Macroeconomic news announcement effects in financial markets.

Evans, Kevin Philip

MACROECONOMIC NEWS ANNOUNCEMENT EFFECTS

IN FINANCIAL MARKETS

KEVIN PHILIP EVANS

Submitted to the University of Wales in fulfilment of the requirement for the Degree of Doctor of Philosophy.

Swansea University

2007

SUMMARY

The interdependence between financial markets and economic fundamentals has formed an important part of financial economics research for many years including the asset pricing, market microstructure and financial econometrics literatures. This thesis contributes to these areas by investigating the impact of macroeconomic news announcements on financial markets through three substantial empirical chapters. In the first, real-time monthly UK macroeconomic variables comprise potential risk factors within a test of the Arbitrage Pricing Theory, the results of which confirm that unexpected inflation and investment uncertainty are significantly priced. The key innovation in this research is the identification of asymmetric risk pricing in the sense that these factors are only priced during periods of the business cycle when their associated risks are most prevalent. The second empirical study utilises high frequency data to assess the very short-run reaction of Euro exchange rates to macroeconomic news announcements. Using this new data set and a wider set of international economic indicators than considered hitherto, this chapter contributes to the literature by modelling simultaneously the intraday patterns, macroeconomic announcement effects and fractional integration in volatility, thereby permitting robust estimation of the effects of news announcements and their associated information surprise on returns and volatility. US news indicators are found to dominate Euro exchange rate volatilities, causing both extreme short lived returns and violent, more persistent increases in volatility. In further exploration of such effects, but in the context of futures markets, the third empirical chapter reported considers a continuous time jump diffusion model and implements very recently developed non-parametric techniques to identify daily jump variation and intraday jumps. Jumps are found to be important components of the price process, through their size, intensity and contribution to quadratic variation. Many jumps are caused by US macroeconomic news and the information surprises delivered by data releases explain vast proportions of these jumps, confirming that news has an immediate impact and that asset prices are indeed closely linked to economic fundamentals.

DECLARATIONS

DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed .... (candidate)

Date ....11/1/08...

STATEMENT 1

This thesis is the result of my own investigations, except where otherwise stated.
All sources are acknowledged, giving explicit references, and a bibliography is appended.

Signed .... (candidate)

Date ....11/1/08...

STATEMENT 2

I hereby give consent for my thesis, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organisations.

Signed .... (candidate)

Date ....11/1/08...

ACKNOWLEDGEMENTS

I wish to convey my sincere thanks to Professor Alan Speight for his continued, unwavering support and expert advice. My decision to embark on this thesis was largely due to Alan's encouragement and willingness to supervise me and I am immensely grateful for the subsequent academic career that this has provided. I hope that a productive research partnership will go some way to repaying his faith.

I must also extend my gratitude to the staff of the Economics Department of Swansea University and Cardiff Business School for their friendly encouragement, support and patience. In addition, scholarships and teaching opportunities at Swansea provided financial support, whilst a reduced workload at Cardiff has allowed me time to focus on this study.

Most importantly, I am especially thankful to my family for their love, support and inspiration.
I chi dwi'n cysegru fy llwyddiant, gyda holl cariad fy nghalon.

CONTENTS

LIST OF TABLES

CHAPTER 4

APPENDICES

LIST OF FIGURES

CHAPTER 2

CHAPTER 3

CHAPTER 4

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The interdependence between financial markets and economic fundamentals has occupied a central role in research in financial economics for many years, dating back at least three decades (Bodie, 1976; Fama and Schwert, 1977 and Castanias, 1979). More recently, the availability of high frequency data has allowed the close examination of immediate and short lived linkages between asset returns, volatility and macroeconomic news announcements, with seminal contributions by Andersen and Bollerslev (1998a) and Andersen, Bollerslev, Diebold and Vega (2003). These developments have spurred new empirical literatures in market microstructure, financial econometric and non-parametric analysis that enable us to improve our understanding of the distributional properties of asset returns and volatility dynamics, which are critical for asset and derivative pricing, portfolio allocation, risk management and forecasting. This thesis builds on these advances by further investigating the relationships between macroeconomic news announcements and financial markets in three independent contexts, which are now outlined in turn. Although each empirical chapter may be viewed independently, the unifying theme running throughout this thesis is the investigation of the responses of financial markets to macroeconomic news announcements, which are important to both investors and policy makers.

1.2 REAL-TIME EQUITY ASSET PRICING

The main objectives of the discipline of asset pricing are to understand and explain the cross-section of historical asset returns in order to predict accurately expected asset returns. The Arbitrage Pricing Theory (APT) developed by Ross (1976) provides both an important development in this area and an alternative asset pricing model to the traditional CAPM, allowing asset returns to be generated by an arbitrary number of risk factors. The recognition of more than one pervasive factor generating returns and the foundation of APT on the much weaker condition of absence of arbitrage rather than equilibrium, together with a lack of evidence to support CAPM (Black et al., 1972, Fama and Macbeth, 1973, Blume and Friend, 1973, Roll, 1977) and the discovery of pricing anomalies are some reasons why the APT is arguably a more suitable alternative than the CAPM. The crucial deficiency of APT, however, is its failure to prescribe the number and identity of the factors generating asset returns. The selection of factors using statistical techniques provides one possible approach, but this attaches no economic meaning to the factors, making it difficult to interpret the theory in economic terms.

An alternative approach is to appeal to economic theory directly in order to determine the factors. In their seminal test of APT, Chen et al. (1986) use US macroeconomic variables such as industrial production, inflation, interest rates and bond yields to measure changes to economic conditions which should affect US stock prices. The principal aim of the first empirical analysis of this thesis (Chapter 2) is to understand the effect of macroeconomic data announcement shocks on UK stock prices. This is performed within the context of APT using macroeconomic variables as risk factors, which involves a joint test of the suitability of APT as an asset pricing model and the importance of macroeconomic surprises as risk factors, and therefore extends the previous contributions of Chen et al. (1986) and Poon and Taylor (1991) to a more modern setting.

According to the weak form of the efficient markets hypothesis (Fama, 1970), asset prices fully reflect all publicly available information and so adjust quickly when new information becomes available. The release of macroeconomic data is therefore an important event for financial markets because it causes agents to adjust their expectations of future business conditions, which causes changes to current asset prices. The innovative contribution of Chapter 2 investigates the importance of macroeconomic data announcements for asset pricing by examining the discrepancy between macroeconomic data collected at different vintages. Real-time data represents the information surprises that financial market participants observe at the time of their trading activity, yet fully-revised data that incorporate many iterative revisions are typically used in empirical finance research. This discrepancy is important for policy makers and forecasters in all sectors of economic research whose decisions and advice rely heavily on the initial data release, but whose performance is judged against fully revised data. The problem is accentuated in the financial markets since asset prices react so quickly to these initial news announcements.

Chapter 2 uses and extends a new UK real-time data set that matches historical stock returns to historical initial data announcements, thereby associating stock price movements with the news that traders would have seen at the time of their trades. The use of real-time data is a new development in empirical finance and a recent application by Christoffersen et al. (2002) has examined the relative importance of economic data recorded at different vintages. Using monthly data for US stock returns and macroeconomic variables, Christoffersen et al. (2002) find this difference to be important and significant for risk pricing. The analysis presented in Chapter 2 further contributes to this literature as the only known investigation of the relationships between real-time and fully-revised macroeconomic factors and stock returns for the UK. Using monthly data, and defining real-time macroeconomic variables strictly by the news that market participants observe, asset prices are indeed found to be linked to news regarding economic fundamentals. Moreover, an innovative extension to the literature finds evidence of asymmetry in the sense that macroeconomic risk factors are significantly priced during episodes of the business cycle when their associated risks are most prevalent.

1.3 EURO FX VOLATILITY AND NEWS

Given the importance of risk in financial economics, the measurement and forecasting of volatility are among the most critical concepts in empirical finance, with direct implications for asset pricing, portfolio theory and risk management. Volatility has become one of the most actively researched areas in time series econometrics and economic forecasting in recent decades. More recently, our understanding, measurement and forecasts of volatility have been advanced tremendously through the availability and application of high frequency financial returns data. Such data is not only important for characterising the real-time trading, pricing and risk management practices used by practitioners in today's liquid financial markets, but also extends our knowledge of market efficiency and market microstructure. At the heart of these areas lies the characterisation of the price discovery process, which investigates the way in which news about macroeconomic fundamentals is incorporated into asset prices. Nowhere is this more important than in the foreign exchange market, where the determination of exchange rates and the link between exchange rates and fundamentals remain the central issues of exchange rate economics. Whilst financial market participants pay close attention to data on underlying economic fundamentals, the apparent difficulty in empirically mapping economic fundamentals to asset prices is remarkable.

Despite the apparent lack of predictive power of fundamentals for asset prices, the largest absolute intraday asset returns are closely linked to the release of macroeconomic news. Such spectacular surges in volatility are short-lived and comprise only one component of intraday returns volatility. High frequency data, therefore, are crucial for the analysis of the behaviour of financial markets at the time of public information arrivals, and the major macroeconomic announcements are dominant in the intervals immediately following news releases. However, when considering the data in its entirety, macroeconomic announcement effects are secondary in explaining overall volatility, their explanatory power being lower than both the distinctive intraday volatility pattern at high frequencies and lower than standard volatility forecasts at the daily level. From an econometric perspective, the robust analysis of macroeconomic announcement effects therefore requires the simultaneous modelling of, and control for all three of these volatility factors. The filtration of high frequency returns volatility through modelling of the underlying pattern is essential in order to isolate the true impact effect and dynamic response to news. This involves adopting a deterministic intraday volatility pattern to capture high frequency volatility periodicity, imposing a predetermined volatility response pattern following each news release, and then assessing the extent to which particular announcements load onto this pattern, so allowing the robust and efficient investigation of a wide range of individual announcements (Andersen and Bollerslev, 1998a, Andersen, Bollerslev and Cai, 2000 and Bollerslev et al., 2000). Very few studies tackle the complexity involved in the simultaneous modelling of all components of intraday volatility, and many discard valuable information relating to macroeconomic news effects by grouping news events into categories.

Chapter 3 contributes to the literature in several ways. First, it uses five-minute bid-ask quotes of the Euro against the US Dollar, UK Pound sterling and Japanese Yen, which constitutes a new market that has yet to be investigated in this econometric framework. Second, the dataset includes a wider selection of macroeconomic news announcements than considered hitherto in the literature, including popular economic indicators from the US, Eurozone, Germany, France, UK and Japan. Third, the chapter compares two alternative techniques for capturing the intraday volatility pattern, the flexible Fourier form (Andersen and Bollerslev, 1998a, Andersen, Bollerslev and Cai, 2000 and Bollerslev et al., 2000), and a cubic spline specification (Taylor, 2004), which has yet to be applied to foreign exchange data. Fourth, the chapter aims to provide a comprehensive characterisation of Euro volatility focusing on its response to a range of macroeconomic announcements that convey varying degrees of news within a turbulent economic and geopolitical background.

More recently, studies have used the information surprise of announcements to investigate the immediate behaviour of exchange rates around the releases of data relating to macroeconomic fundamentals. Modelling the dynamics of high frequency returns volatility contributes to a robust econometric methodology for analysing the response of conditional means to news, thus allowing an investigation of the links between macroeconomic fundamentals and asset prices. Andersen, Bollerslev, Diebold and Vega (2003) show that macroeconomic news announcements generate very large, statistically significant, rapid exchange rate movements, characterised as conditional mean jumps. Moreover, news announcements relating to US economic fundamentals explain large proportions of these jumps. Chapter 3 extends this research across a wider range of announcements than previously considered, performing the analysis over the full time series and also for a sub-sample that focuses on a window around announcements.

1.4 JUMPS AND NEWS IN FUTURES MARKETS

The distributional properties of daily or lower frequency asset prices along with the dynamics of asset price volatility have been the most widely studied topics in financial economics recently, with important implications for the risk-return trade-off and asset pricing, portfolio allocation, risk management techniques and derivative pricing. One stylised fact emerging from empirical studies reveals that discretely sampled asset prices exhibit extreme violent movements, or outliers, rendering their unconditional returns distributions with fat tails relative to the Gaussian distribution. Meanwhile, the empirical regularities surrounding the volatility of discretely sampled asset returns are temporal dependence, persistence, clustering and a volatility feedback (or leverage) effect. Despite these advances, it is widely recognised that the most important developments in theoretical asset pricing have been based on continuous-time methods. The early studies aimed to provide continuous-time models that were more realistic in explaining these salient characteristics of return distributions. Specifically, Merton (1976) advocated the need to explicitly incorporate discontinuities, or jumps, in the price process, whilst Hull and White (1987) highlighted the importance of including time varying diffusive volatility. The more recent advances demonstrate the need to incorporate both factors to improve empirical performance, suggesting that price processes are best described by jump-diffusion models comprising a smooth, slowly mean reverting continuous sample path and a less persistent jump component.

The availability and application of high frequency asset price data has sparked a rapid growth in the non-parametric literature which harnesses the tremendously useful information contained within high frequency returns to measure realised volatility at the daily frequency more accurately. In the framework of arbitrage free continuous-time jump-diffusion models, realised volatility utilises high frequency data to provide a consistent estimate of the quadratic variation of the prices process, which includes the variation due to jumps. In the very latest developments, Barndorff-Nielsen and Shephard (2004b, 2006) provide a non-parametric measure of realised bipower variation, which is a consistent estimator of the continuous sample path, thereby isolating this component of quadratic variation. The importance of this result is that the difference between empirical measurements of realised variation and bipower variation generates a consistent estimate of the jump variation. Since this procedure limits jump detection to identify at least one jump on a particular trading day, the method has been focussed on improving our understanding of asset price dynamics and volatility at the daily frequency. However, the very recent works of Andersen, Bollerslev and Dobrev (2007) and Andersen, Bollerslev, Frederiksen and Nielsen (2006) extend this notion to allow the possibility of multiple intraday jumps and the identification of their exact timing. This is important in their studies for adjusting high frequency returns series for these jumps, to eliminate the impact of outliers, before transforming this jump-adjusted series into 'financial' time, to annihilate the volatility feedback effect, before confirming that the distributional properties of appropriately adjusted returns are Gaussian.

Whilst the recent studies of Barndorff-Nielsen and Shephard (2006) and Andersen, Bollerslev and Diebold (2007b) suggest links between macroeconomic news announcements and daily jump variation measures, a detailed investigation of the association of macroeconomic innovations and jumps has yet to be undertaken. The empirical analysis reported in Chapter 4 aims to fill this void whilst combining several strands of the recent asset pricing and financial econometrics literatures. The theoretical framework presented is built on the foundation of an arbitrage free jump-diffusion continuous-time model. In this context, and implementing high frequency data across an extensive range of international futures markets, Chapter 4 adopts alternative non-parametric jump identification procedures to investigate the relative importance of jump intensity and magnitude as a component of total price variation. Furthermore, Chapter 4 implements a range of intraday jump detection techniques to locate the precise timing of jumps and provides an innovative contribution to the recent literature by assessing the extent to which both pure announcements and the informational surprise delivered by those announcements cause jumps and explain their magnitude. Chapter 4, therefore, explores economic explanations for the presence and magnitude of jumps and offers further insight into the links between asset prices and economic fundamentals.

1.5 OVERVIEW OF THESIS

The remainder of this thesis is structured as follows. Following this brief introduction, the three substantive empirical exercises contained in Chapters 2-4 each comprise a more extensive introduction to and motivation for the respective topic, a survey of the relevant theoretical and empirical literature on that topic, an explanation of the method of analysis, data sources and results, and a summary of the research findings and conclusions. Finally, Chapter 5 summarises and unifies the findings of the thesis and offers some tentative suggestions for possible future research.

CHAPTER 2

REAL-TIME RISK PRICING OVER THE BUSINESS CYCLE: SOME EVIDENCE FOR THE UK

ABSTRACT

Revisions to macroeconomic data are often large and occur for many months after the initial data announcement. Empirical finance research incorporating macroeconomic variables typically use only fully-revised data; however, fully-revised data do not reflect the true information available to forecasters, policy makers and financial market participants at the time of their decision-making. This chapter uses new, real-time data on macroeconomic variables to assess the relative importance of different vintages of data on macroeconomic variables as determinants of UK stock returns using the framework of the Arbitrage Pricing Theory. Results obtained using fully-revised data imply that macroeconomic innovations are not important for the pricing of stocks. However, results obtained using real-time data reveal that both unanticipated inflation and uncertainty surrounding the investment climate are significant factors driving equity returns, and that their pricing influence is only present during phases of the business cycle when those risks are most prevalent.

2.1 INTRODUCTION

The main objectives of finance and more specifically the discipline of asset pricing are to understand and explain the cross-section of historical asset returns and to predict accurately expected asset returns. The Capital Asset Pricing Model (CAPM) introduced independently by Sharpe (1964), Lintner (1965) and Mossin (1966) was a popular leader in this field, using equilibrium conditions to determine the cross-section of expected asset returns based on a single risk factor: the covariance between an asset's return and the return on a market portfolio.

The Arbitrage Pricing Theory (APT) developed by Ross (1976) provides an alternative model, allowing asset returns to be generated by an arbitrary number of risk factors according to the equation:

$$r_{\psi} = \beta_{0,\psi} + \sum_{k=1}^{K} \beta_{k,\psi} F_k + e_{\psi} \,, \tag{2.1}$$

where r_{ψ} denotes the return on asset ψ; F_k are zero mean risk factors generating returns which are common to all assets; $\beta_{k,\psi}$ is the sensitivity of the return on asset ψ to factor k; $\beta_{0,\psi}$ represents the expected return on asset ψ and e_{ψ} are zero mean, asset specific disturbances, which are assumed to be uncorrelated with F_k and each other. The model relies on the absence of arbitrage opportunities and an infinite number of assets to derive the following linear pricing rule for expected returns:

$$R_{\psi} = \lambda_0 + \sum_{k=1}^{K} \lambda_k \beta_{k,\psi} \,, \tag{2.2}$$

where R_{ψ} denotes the expected return on asset ψ; λ_k represents the market price of risk factor k, the product $\lambda_k \beta_{k,\psi}$ is the risk premium associated with risk factor k and λ_0 is the return on the risk free asset.

There are many reasons why the APT is believed to be a more suitable alternative to the CAPM. The first is the recognition of more than one pervasive factor generating returns, which expands the idea of diversifiable and non-diversifiable risk beyond the consideration of only an unobservable market portfolio. Secondly, APT is founded on the much weaker condition of absence of arbitrage rather than equilibrium and does not require explicit definitions of investor preferences. There is also a lack of evidence to support CAPM in such works as Black et al. (1972), Fama and Macbeth (1973), Blume and Friend (1973), Roll (1977) and many papers that discover a range of pricing anomalies. Finally, the APT is a popular model with empiricists because it can easily be applied to empirical techniques.

The crucial deficiency of the APT, however, is its failure to describe the number and identity of the factors generating asset returns. The selection of factors using statistical techniques provides one possible approach, but this attaches no economic meaning to the factors, making it difficult to interpret the theory in economic terms. An alternative approach is to appeal to economic theory directly in order to determine the factors. Since, in principle at least, the prices of financial securities are calculated as the present value of future expected cash flows, any variable causing changes to future economic conditions or the discount rate should be a factor influencing asset return dynamics. In their seminal paper, Chen et al. (1986) therefore use US macroeconomic variables such as industrial production, inflation, interest rates and bond yields to measure changes to economic conditions which should affect US stock prices. Their method is followed closely in this study in order to further our understanding of the links between financial markets and the real economy, focusing on the UK stock market.

According to the weak form of the efficient markets hypothesis proposed by Fama (1970), asset prices fully reflect all publicly available information and so adjust quickly when new information becomes available. The release of macroeconomic data is therefore an important event for financial markets because it causes agents to adjust their expectations of future business conditions, which causes changes to current asset prices. Agents use currently available information, which includes all previous data releases, to form expectations of these data announcements. If current asset prices fully reflect these expectations, prices will only move if expectations are adjusted, which will only occur if the news is unanticipated. The principal aim of this chapter is to understand the effect of macroeconomic data announcement shocks on UK stock prices. To examine this relationship, it is important to measure accurately the proportion of the announcement that has already been anticipated so as to leave only the innovation or shock to the variable which is not yet impounded in stock prices. The econometric modelling of expectations is also put under scrutiny.

The final and most innovative motivation of this chapter concerns the discrepancy between preliminary macroeconomic data announcements and fully-revised data sets which are typically used in empirical finance research. Data describing real activity, for example Gross Domestic Product (GDP) and industrial production, are often revised for many months after the initial announcement to reflect the more accurate information that becomes available over time. This creates problems for policy makers and forecasters in all sectors of economic research whose decisions and advice rely heavily on the initial release. The problem is accentuated in the financial markets because the transfer of information occurs so quickly. Expectations of business conditions and stock prices respond immediately to the initial data release. This chapter uses a new real-time data set that matches historical stock returns to historical preliminary data announcements, associating stock price movements with the news that traders would have seen at the time of their trades. Until only very recently, finance research using macroeconomic variables has used fully-revised data because these are the series that are currently available and most accessible. Fully-revised data provide the most accurate description of past economic conditions, but they do not measure the true information that was available to investors, which is so important in stock pricing, and so they cannot be contemporaneously linked to stock returns. The use of real-time data is a new development in empirical finance and it is hoped that, when used in parallel with fully-revised data, it will show that results and interpretations of financial research are sensitive to the choice of macroeconomic data type.

The remainder of the chapter is organised as follows. The next section details the previous literature relating to tests of the APT, economic variables as determinants of stock prices and the effects of data revisions. The methodology is then explained in section 2.3, including a detailed description of the data and justification for the econometric procedure used. Empirical findings and interpretations are listed in section 2.4 and are checked for robustness before some concluding remarks are made.

2.2 LITERATURE REVIEW

The sheer volume of research dedicated to the APT, from theorists and empiricists alike, is testament to its importance as an asset pricing model and as an alternative to the CAPM. Ross (1976) was the first to derive an approximate linear pricing rule for expected asset returns using a multifactor return generating process, subject to the condition that no arbitrage opportunities exist. But the APT linear pricing rule only holds as an exact relationship as the number of assets in the economy increases without bound, a restriction that has caused the validity of early empirical studies to be questioned. Shanken (1982), in particular, argues that since any test of APT can only use a finite sample of assets, the fundamental assumptions of the model imply that deviations from the linear pricing rule may be large. If large deviations in pricing are permitted using a finite sample, there can be no criteria for rejecting APT in empirical tests and APT cannot be tested.

In response, Conner (1984) introduced a multifactor model founded on competitive equilibrium and obtained an exact pricing relation and hence an empirically testable theory. Crucial to this derivation, though, are the re-emergence from a CAPM style framework of explicit definitions of investor tastes and the market portfolio. Whereas Ross (1976) assumes that idiosyncratic risk can be fully diversified away if the economy is made up of a large number of assets, Conner (1984) asserts that idiosyncratic risk is diversified away in the market portfolio. Reliance on the properties of the market portfolio, however, exposes the model to the Roll (1977) critique that has plagued tests of CAPM, that the inability to observe the true market portfolio precludes any tests of CAPM. In more intuitive derivations of the model, Grinblatt and Titman (1983) and Dybvig (1983) find that theoretical deviation from APT pricing is negligible in a realistic finite economy and that the APT provides a good approximation for the mean returns of all traded assets. They do not rely on equilibrium based derivations of APT, a subject that Dybvig and Ross (1985) and Shanken (1985) debate, but do argue that an exact pricing relation can exist, which means that the APT can be tested.

Fama (1991) famously described multifactor models as "an empiricist's dream" because they allow the investigation of relations between cross-sectional returns and any set of factors that are correlated with returns. The problem with multifactor models, though, is "our complete ignorance of their [the factors'] identity".[1] Both statistical and theoretical approaches have been proposed to define the number and the identity of the return generating factors, and these are reviewed in the following sub-sections, before moving on to consider macroeconomic factors

[1] Chen et al. (1986), p.384.

as determinants of stock returns and the problems associated with macroeconomic data revision.

2.2.1 Statistical Approach

The first and most popular statistical method uses factor analysis to estimate the risk factors (F_k) and their loadings ($\beta_{k,\psi}$) simultaneously. Each factor is a weighted average of the returns earned on the securities under examination. The analysis determines a specific set of factors and loadings which minimises the covariance of residual returns. The number of factors thought to influence returns is hypothesised arbitrarily and different solutions may be obtained by adding more potential factors. Factors are added until the probability that the next factor explains a significant proportion of the covariance matrix drops below some subjective critical level. Once the factor loadings have been estimated, the market price of risk associated with each risk factor (λ_k) can then be estimated in cross-sectional regressions.

Roll and Ross (1980) were among the first to use this technique for testing APT and find that at least three, but probably no more than four factors are important for pricing. More than one priced factor provides empirical support for the APT over CAPM. Roll and Ross (1980) also find support for APT against a specified alternative multifactor hypothesis in that the standard deviation of individual asset returns (a measure of diversifiable risk) was not a priced factor when added to the cross-sectional equation. Only systematic risk (non-diversifiable risk) is found to affect expected returns and this emphasises the main intuition behind APT. Chen (1983) corroborates this positive performance arguing that APT picks up some of the pricing information missed by the CAPM. In addition, firm size and the variance of own firm returns, two spurious variables, do not add explanatory power, supporting the notion that only systematic risk factors should be priced. Cho et al. (1984) provide further evidence in support of multifactor models. They repeat the Roll and Ross (1980) methodology using data from a later period and find that "there do appear to be influences in the market that generate returns beyond those depicted in the zero beta CAPM".[2] Lehmann and Modest (1988) note that when using a large number of securities, it is computationally infeasible to obtain consistent estimates of factor loadings when using factor analysis. To combat this, they "employ the EM

[2] Cho et al. (1984), p.2.

[Expectation-Maximisation] algorithm of Dempster et al. (1977)" allowing them to study larger cross-sectional data sets than previous tests of APT.[3] Crucially, they find that the APT explains the expected return on portfolios formed on the basis of dividend yield and own variance that the CAPM fails to explain.

Amidst this empirical support, it is important to remember that in the absence of any theory to dictate the identity of the relevant factors, any test of APT is jointly testing the theory itself and the methodology used to determine the factors. Factor analysis, the most common approach, has been criticised. For example, Shanken (1982) disputes the method on theoretical grounds. He argues that a finite set of securities could be repackaged arbitrarily to produce a new set of securities with a new set of returns. Factor analysis could then produce a corresponding factor model in which the factors could be any random variables, not necessarily the same as those identified for the original set of securities. Dhrymes et al. (1984) examine the findings of Roll and Ross (1980) and find that when analysing subgroups of securities the number of relevant factors increases as the number of securities in the subgroup increases. Furthermore, these factors may not necessarily be the same as those identified in a second subgroup. They also question whether the pricing relation is testable when using factor analytic procedures and conclude that the APT's "ability to explain the relevant empirical evidence is not markedly superior" to that of the CAPM.[4]

In response, Roll and Ross (1984) argue that it is not the number of factors that is important, but their effect on pricing and their ability to explain expected returns, particularly against alternative hypotheses. In their reply, Dhrymes et al. (1985) suggest that not only the number of extracted factors, but also the number of priced factors is positively related to the length of the time series of the study and the size of the subgroup of assets used. They also find evidence that idiosyncratic measures, such as unique or total standard deviation, perform better as priced factors than the common factors derived by factor analysis.

In light of the shortcomings of the factor analysis approach, Connor and Korajczyk (1988) present a test of APT using a principal components technique to select risk factors. Principal component analysis uses historical asset returns to form an index that best replicates the variation of the original data. The process continues

[3] Lehmann and Modest (1988), p.223.
[4] Dhrymes et al. (1984), p.323.

to select sequentially uncorrelated indices that best reproduce that variation in the original data which is not explained by the components already identified. These indices or components are the common factors generating asset returns. Connor and Korajczyk (1988) provide empirical support for APT by identifying more than one priced factor. Whilst they suggest that APT performs better than the CAPM in explaining expected returns, "some statistically reliable mispricing of assets by the APT remains."[5]

Many of the empirical studies using statistical approaches support the APT because more than one factor is important for pricing, but the debate over the number and true identity of the common factors remains unresolved. Furthermore, three flaws in these statistical approaches seriously undermine the contribution of these studies. Firstly, no meaning can be attributed to the signs of the estimated coefficients, which means that the signs on the λ_k's and $\beta_{k,\psi}$'s could be reversed without loss of explanatory power. Secondly, the scaling of the λ_k's and $\beta_{k,\psi}$'s is arbitrary, since one could be doubled and the other halved without affecting the results. Third, there is no guarantee that the factors will be identical in different samples and the factors may not be produced in the same order between samples when factor analysis is used. Using statistical constructs as factors, therefore, hampers any economic interpretation of the common factors, a deficiency that has given rise to a more theoretical approach to testing the APT.

2.2.2 Theoretical Approach

In contrast to the purely statistical techniques described above, a theoretical approach specifies the pervasive factors before estimation begins. Factors can be specified in three different ways: as the characteristics of firms that are found to cause anomalies in CAPM pricing; by the construction of portfolio returns based on firm characteristics that mimic common risk factors; and the identification of variables dictated by economic and financial theory.

Empirical anomalies are often found in tests of the CAPM and occur when variables added to the model are found to improve the explanation of the cross-sectional variation of returns. Although possibly spurious or the result of data mining, these anomalies may be viewed as evidence that the CAPM is invalid

[5] Connor and Korajczyk (1988), p.255.

because more than one risk factor appears to influence expected returns. Banz (1981) was first to document the size effect that smaller firms, measured by total market value, tend to have higher risk adjusted returns than larger firms. Basu (1977) investigated the relationship between common stocks and their price-earnings ratio (P/E) and found that low P/E portfolios tend to earn higher returns, both absolute and risk adjusted, than high P/E portfolios. The significance of returns-size and returns-earnings yield (E/P) relationships are both supported by Reinganum (1981), but when considered jointly he finds that the size effect dominates the earnings yield effect. Hawawini and Keim (1997) also list studies showing evidence that stock returns are related to firms' cash flow-price and price-sales ratios, both thought to be variations on the earnings yield variable. A significant negative relationship between the ratio of price per share to book value per share (P/B) and stock price has also been found (Fama and French, 1992) along with a significant positive relationship between returns and dividend yield (Ball, 1978 and Litzenberger and Ramaswamy, 1979).

Other anomalies suggest that excess returns can be earned by following different trading strategies. Jegadeesh and Titman (1993) suggest that a momentum strategy of buying stocks that have performed well in the past (winners) and selling those that have performed poorly in the past (losers) generates positive and significant returns. De Bondt and Thaler (1985, 1987) present evidence for the reverse (contrarian) strategy of buying losers and selling winners, founded on their belief that investors overreact to unexpected or dramatic news events. Hawawini and Keim (1997) provide an excellent review of the evidence for anomalies, including international studies, and can verify the existence of some of them with statistical research of their own.

These studies discover stock return relationships that are not explained by the CAPM and imply its rejection as an asset pricing theory. Sharpe (1982) was first to apply these findings to a multifactor framework. He considered a list of firm characteristics (firm's beta with the S&P Index, size, dividend yield, beta on long term bonds, past return and eight sector membership variables) and found that explanatory power of the model was increased as more variables were added. Fama and French (1992) find similar evidence for APT as "size and book-to-market equity combine to capture the cross-sectional variation in average stock returns associated with beta, size, leverage, book-to-market equity and earnings-price ratios."[6] Fama and French (1993) extend their analysis to investigate returns on bonds as well as stocks and find five common risk factors that explain the variation of cross-sectional returns: a market factor, firm size and book-to-market (B/M) equity are found to describe stock returns, and maturity and default risk measures are found to explain bond returns.

There is plenty of evidence to suggest that more than one factor is influencing returns, but the discovery of firm characteristics as factors is not founded on economic reasoning. This is recognised by Fama and French (1996) when they introduce their three-factor model. The model suggests that stock returns in excess of the risk free rate are explained by three factors: a firm's beta with the market portfolio, firm size, and firm book-to-market ratio. They argue that this parsimonious model captures much of the cross-sectional variation in average stock returns, absorbs many of the anomalies discussed above that have plagued the CAPM, and is an equilibrium pricing model, and thus a three-factor version of APT. Chan et al. (1998) replicate these findings and show their robustness in international tests. The measures of firm size and B/M ratio are constructed as returns to portfolios formed on the basis of each characteristic and are, at best, interpreted as variables that mimic the true underlying pervasive factors.

Although there is empirical support in favour of APT, there still remains debate as to the exact number of factors and their true identity. Chen et al. (1986) address this identification problem by deriving macroeconomic news variables from economic and financial theory to define more explicitly the underlying risk factors driving asset returns. Over their entire sample, the monthly growth rate of industrial production, unexpected inflation and a default risk premium are all significantly priced, whereas the term structure of interest rates was only marginally significant. Using data for the UK, Poon and Taylor (1991) aim to uncover out of sample evidence to support the findings of Chen at al. (1986). They cannot corroborate the US evidence and suggest that either other macroeconomic factors may be at work in the UK or that the methodology proposed by Chen et al. (1986) is inadequate to detect such relationships. Shanken and Weinstein (1987), using the same data set but different estimation techniques to Chen et al. (1986), found that industrial production

[6] Fama and French (1992), p.427.

and default risk were not priced factors. Hamao (1988) investigated the Japanese stock market and found pricing evidence similar to Chen at al. (1986), although such relationships may be spurious due to neglected serial correlation in the macroeconomic and financial market factors. Martinez and Rubio (1989) found no significant relationships using Spanish data, supporting the evidence of Poon and Taylor (1991). More recently, Chan et al. (1998) have shown that other than a default risk measure and an interest rate spread, macroeconomic factors perform poorly, and this is confirmed in the Japanese and UK markets. The relative lack of international tests of APT, using macroeconomic and financial market variables as risk factors, coupled with the mixture of evidence presented, provides a clear motivation for further empirical research in this field.

2.2.3 Macroeconomic Variables and Stock Market Returns

The hypothesis that stock market returns are closely related to macroeconomic variables has strong intuitive appeal, but evidence from empirical investigations is mixed. Castanias (1979) showed that market returns appear to be more variable on the arrival of macroeconomic information and that the market moves quickly to impound specific macroeconomic information into asset prices. Bodie (1976) documented a negative relationship between the real return on equity and expected and unexpected inflation, implying that to be used as a hedge against inflation equity would need to be sold short. Fama and Schwert (1977), Schwert (1981), Fama (1981) and Khil and Lee (2000) document a similar negative relation between stock returns and inflation. Schwert (1981) only finds a negative relation of small magnitude, but notes that stock prices respond to the news announcement of inflation, which occurs several weeks after the data are collected. Fama (1981) suggests that real stock returns and measures of real activity are positively related and that the negative relation between inflation and stock returns is induced by a negative inflation-real activity effect. This effect is stronger for future values of real activity, suggesting that the stock market leads the real sector or offers a barometer of future economic performance. Reinforcing Fama's (1981) assertions, Khil and Lee (2000) find that real stock returns and inflation are negatively correlated in ten Pacific-rim countries. In addition, in nine of these countries they find that the negative stock return-inflation pattern is driven by real output disturbances, which dominate the positive relation induced by monetary disturbances.

Pearce and Roley (1985), in contrast, do not find a strong negative stock return-inflation relation. Using survey data to measure expectations, they find support for the efficient market hypothesis where only unanticipated announcements affect stock prices. However, only news about the money supply and the discount rate are significant, real output having no impact on stock prices, and inflation showing only a limited effect. Fama (1990) finds that future production growth rates explain a large proportion of the variation in stock returns, which is supported by Schwert (1990a), but when considering a range of economic indicators Ferson and Harvey (1991) find that the most important variable for capturing the predictable variation in stock returns is a stock market risk premium. There is also a noticeable absence of real activity news measures in the six candidates for priced factors that Flannery and Protopapadakis (2002) find. Specifically, they argue that news of three nominal factors (consumer price inflation, producer price inflation and a monetary aggregate) and three real factors (the balance of trade, employment report and housing starts) are priced factors. Lamont (2001), however, does find correlation between monthly stock returns and US output, consumption, labour income and inflation. Rather than trying to explain the variation in stock returns, Lamont (2001) constructs portfolios of stock returns that track economic variables and finds that these tracking portfolios can be useful in forecasting macroeconomic variables.

When investigating the size effect of New York Stock Exchange (NYSE) firms, Chan et al. (1985) find that a multifactor model can explain the variation of returns with the most important variable being a default risk premium. Smaller firms tend to have higher returns than larger firms because smaller firms are more susceptible to changing economic conditions. The change in conditions is best measured in this case by the spread of yields on low grade corporate bonds over yields on government bonds. Campbell (1987) makes the case for the term structure of interest rates as a predictor of excess stock returns and Chen (1991) argues for a role for both a term structure spread and a default risk spread in describing the variation of stock returns.

There is some evidence that real activity, inflation, a term structure premium and a default premium measure changes to economic conditions that impact stock returns, but the evidence is not conclusive. Some relationships are strengthened by allowing the response of stock prices to economic news to be asymmetric over the course of the business cycle. Fama and French (1989), for example, state that expected returns on common stocks contain a term or maturity premium that has a clear business cycle pattern and, because of this, expected returns are lower (higher) when economic conditions are strong (weak). McQueen and Roley (1993) investigate this asymmetric response using a wider range of economic variables. They find little evidence that macroeconomic news influences stock prices, but they do recognise that the relationships become stronger if they allow for different stages of the business cycle. When the economy is strong, stock returns are negatively related to real activity, which McQueen and Roley (1993) attribute to the effect of anticipated tighter monetary policy, and thus higher discount rates, dominating the influence of higher expected future earnings. Boyd et al. (2001) address the same issue but consider only news of unemployment. They argue that the relative importance of discount rate and cash flow effects on stock prices changes over time depending on the state of the economy. The discount rate effect dominates in an expansion while the cash flow effect dominates in a contraction.

In summary, there is some evidence that news about inflation, interest rates and default risk are related to stock returns. Evidence for the inclusion of real activity as a factor describing the variation in stock returns is sparse. This may be because studies do not allow responses to news to vary over the business cycle or use data that does not accurately represent the informational flow to the stock market. Conventionally, empiricists use macroeconomic data sets that are currently available and are fully-revised. Revisions to data announcements can sometimes be large and often occur for many months after the data release. A fully-revised time series may not, therefore, reflect the news that stock market participants would have seen at the time of the initial data release. Data accuracy, especially in financial markets that digest new information so quickly, is a crucial issue and previous work focusing on this issue is reviewed in the next sub-section.

2.2.4 Data Revisions

The problem of revisions to data announcements has been recognised and studied for many years. Zellner's (1958) statistical analysis of the difference between provisional and revised estimates of US Gross National Product (GNP) was the seminal paper and prompted a sizeable work from Morgenstern (1963). Although descriptive analysis of this discrepancy is insightful, the bulk of the subsequent literature has focused on the difficulties for economic forecasting and policy decisions of using initial rather than revised data.

Considering forecasting first, Stekler's (1967) evidence that preliminary data are useful for economic analysis has been strongly refuted. Cole (1969), for example, finds that "the use of preliminary rather than revised GNP data impaired forecasting accuracy and by a substantial amount."[7] Howrey (1978) also finds evidence that preliminary data help to improve prediction accuracy, but only if a model incorporating the distinction between preliminary and revised data is used. However, most other researchers find that forecasts based on preliminary data are not as accurate as those using fully-revised data. In an analysis of the forecasting ability of the composite leading index for macroeconomic variables, Diebold and Rudebusch (1991) find that forecasting performance deteriorates when using real-time data. Money is not useful for predicting output, according to Amato and Swanson (2001), who find that the successful predictive power of recently revised data is not duplicated in real-time data. Mankiw et al. (1984) find evidence that subsequent revisions to measures of the US money stock are predictable based on real-time information, concluding that preliminary announcements are not rational estimates of the true money stock. Patterson and Heravi (1991) examine a similar issue using data on the expenditure components of UK GDP collected at different degrees of revision, or vintages. They find that the history of revisions has predictive power for the fully-revised vintage.

Given that fully-revised data is more accurate than initial release data, making use of more information becoming available over time, it is no surprise that forecasting performance improves when using fully-revised data. The problem facing forecasters is that they are restricted to forming estimates using only preliminary data. The same time constraint applies to policy makers, who are forced to set economic policy based on the informational content of initial data releases. Surprisingly, Federal Reserve policy decisions during the 1970s, according to Maravall and Pierce (1986), would not have been different had fully-revised data been available to them. Despite their size, they argue, revision errors seem to have little impact on the setting of policy. Runkle (1998), in contrast, concludes that in order to understand policy decisions, researchers must use initial data. He uses US

[7] Cole (1969), p.79.

GDP and inflation to investigate the size of revisions and their implications for researchers trying to understand economic performance and the reactions of policy makers. Similarly, Perez (2000) finds that real-time data are more effective than fully-revised data for describing the information set used by the Federal Reserve policy makers.

Forecasting and policy making rely on preliminary data announcements and the effects of data revisions have been studied extensively already. However, the effect of preliminary releases of macroeconomic data on financial markets has only recently begun to be investigated. Using a real-time data set presented by Croushore and Stark (2001) and following the empirical methods of Chen et al. (1986), Christoffersen et al. (2002) have recently examined the sensitivity of asset prices to quarterly real-time economic news. Their main finding is that the choice of data used to construct macroeconomic variables has a dramatic influence on the empirical results, although by leading some of their real output variables they violate the real-time framework. The application of real-time macroeconomic data to financial studies is an innovative area of economic research, which is to be followed here. By extending the UK real-time data presented by Eggington et al. (2002), the aim of this paper is to apply higher frequency monthly data that is more likely to capture the sensitivity of asset returns to macroeconomic innovations, whilst maintaining a strict emphasis on the contemporaneous relationship between stock returns and the information set available to traders. Results and interpretations that vary between fully-revised and real-time data sources will also provide out of sample support to the evidence documented by Christoffersen et al. (2002).

2.3 METHODOLOGY

The first aim of this chapter is to identify empirical support for the APT, which allows asset returns to be generated by an unspecified number of risk factors. From the wide choice of potential factors available, this study focuses on unexpected macroeconomic news as risk factors, thereby investigating the intuitive links between financial markets and the real economy.

Rational agents form expectations of future economic conditions based on all publicly available information. Asset prices fully reflect these expectations and adjust only when unanticipated information is published. When associating macroeconomic data with asset prices, it is important to extract the component of data announcements that is unexpected, measured by the difference between the actual release and the expectation. Measuring expectations accurately is therefore an important step and alternative expectations models will be used to test whether the results of this test of APT are dependent upon the choice of expectations model.

The remainder of this section explains the data on stock prices used, describes the construction of the relevant macroeconomic factors, explains the precise difference between the two data sets, and details the econometric techniques used to test whether macroeconomic news shocks represent systematic risks that are priced by the UK stock market.

2.3.1 Stock Prices

Under certain simplifying assumptions, the long-standing discounted cash flow model values the current stock price as the present value of the cash flow that a stockholder expects to receive from the stock. This implies that a simplistic discounted cash flow model values stock γ according to:

$$p_{\gamma,t} = \sum_{m=1}^{\infty} \frac{D_{\gamma,t+m}}{(1+\theta)^m}, \tag{2.3}$$

where the share price in period t, $p_{\gamma,t}$, is the infinite sum of discounted values of the firm's future expected dividends, $D_{\gamma,t+m}$, with m referring to the future periods following t. The discount rate, θ, is the rate of return investors require to induce them to purchase the asset, and this reflects both the time value of money and the appropriate level of risk of the stock.[8] The discount rate can also be interpreted as an opportunity cost, representing the rate of return foregone by an investor in the next best alternative asset with comparable risk. It is intuitive from the pricing formula that stock prices are determined by two variables: expected future earnings, which are eventually paid out as dividends, and the rate at which those dividends are

[8] The simplifying assumptions referred to in the text are, amongst others, that expected stock returns and the discount factor are constant, that rational speculative bubbles are precluded such that dividend growth is stable, and that 'noise traders' are precluded, such that all investors adhere to the same view of the determinants of returns and have homogeneous expectations. However, whilst it is important to recognise that the discounted cash flow model is a simplistic paradigm of equity pricing, not least since some firms may not pay dividends and the discount rate itself is likely to include a term structure, it must be emphasised that the purpose of considering this simplistic framework here is purely to motivate consideration of the pervasive macroeconomic factors most likely to influence the cross-section of expected stock returns.

discounted.[9] The APT assumes that asset specific risk can be fully diversified away so only innovations to macroeconomic variables that cause changes to expected dividends or the discount rate across all stocks should move stock prices. Following Chen et al. (1986) and Christoffersen et al. (2002), real output, inflation, the term structure of interest rates and a risk premium are the factors selected. The use of macroeconomic data in empirical research begets the problem of data revision. In respect of this, the following work contains two parallel investigations using different data sets to study the sensitivity of data selection for financial studies.

End of month stock prices from December 1979 to October 2002 were extracted from Thompson Financial's Datastream Advance (Datastream). Prices include dividends and are adjusted for corporate actions. All stocks listed on the Financial Times Stock Exchange that are available in the Datastream database are included. New firms are added to the sample when their shares are issued and the data include the stock prices of de-listed and failed firms, which minimises any survivorship bias in the data. To enable comparison between stocks, percentage returns are calculated as the difference between consecutive logarithmic prices, $r_{\gamma,t} = \ln(p_{\gamma,t}) - \ln(p_{\gamma,t-1})$.

2.3.2 Macroeconomic Factors

2.3.2.1 Real Output

Real output surprises affect stock prices through their influence on expected dividends. An unanticipated permanent increase in the rate of productive activity will raise expected future earnings across all stocks and lift current stock prices and hence stock returns. Changes in real output activity are measured by the growth rate of industrial production. Although quarterly real-time GDP figures are available for the UK, we focus on monthly data that is more likely to capture the responsiveness of stock returns to macroeconomic innovations and avoids the statistical issue of interpolation. We would prefer to use an indicator for real output that reflects both the openness of the UK economy and increased importance of the service sector, but this data is either unavailable at the monthly frequency or does not span the duration of our sample. Seasonally-adjusted monthly levels of the index of output for all

[9] There is a long history of discussion in the academic literature about what should be discounted. Some authors argued earnings, some dividends, and others earnings plus non-cash expenses such as depreciation. It turns out that, properly defined, these approaches are equivalent. See Miller and Modigliani (1961).

production industries are collected from the Office for National Statistics (ONS) from January 1979 to October 2002. Time series of month on month and year on year growth rates are calculated as the difference between appropriate logarithmic index levels and begin from January 1980.

The index of industrial production for a particular month is published 26 working days after the end of that month. Production index levels or their associated growth rates for month t, therefore, are announced in the later month $t+i$ and this represents the initial or preliminary release. On this release date in month $t+i$, the index levels announced in previous months might be revised if more accurate data has become available to the ONS. These revisions are often substantial and can occur for many months after the initial release. In empirical work, economists are constrained to the use of historical time series and conventionally use fully-revised series. Production in a particular month t will be announced in month $t+i$, but when the data are collected in month n, later than the end of the sample, the figure announced in month $t+i$ is likely to have been revised many times since its original publication. More formally, the fully-revised industrial production index level or growth rate can be represented by ${}_ty_n$, which denotes the production index for month t announced in month $t+i$ and revised in many subsequent months until it is collected in the vintage month, n. If the data were collected today, the data vintage, n, would refer to the current month and the series would be recorded at the current vintage. The succeeding observation of the current vintage series would be ${}_{t+1}y_n$ showing the production level for month t+1 fully-revised by the time of collection in vintage month n. Since revisions to variables can be announced up to month n, this series does not reflect accurately the information that stock market traders would have seen when trading in month t. For this study, the fully-revised series of industrial production index levels was gathered from ONS on 4th December 2002 with 1995 as the base year of the index.

Of much more informational value for a financial study is the time series of industrial production measured in real-time. This is a time series of preliminary announcements matching the industrial production data release witnessed in month t with stock returns for month t, even though the production data relate to activity for the previous month $t-i$. Crucially, the real-time data represent the news that stock market traders would have seen in a particular month, which is likely to be much more important in influencing stock prices than the fully-revised series that is not observed until much later. More generally, a real-time observation of industrial production growth can be represented as ${}_{t-i}y_t$ indicating the value of or growth in the index measuring activity in month *t-i* that is released in the real-time vintage month *t*. The subsequent observation of the real-time series would be ${}_{t-i+1}y_{t+1}$. Real-time data on industrial production from January 1980 to June 1999 were obtained from Eggington et al. (2002). The data have been extended here to October 2002 using the ONS Economic Trends publication. The vintage month of the data refers to the month of publication of Economic Trends and hence the month during which the data became available to stock market traders. Monthly and annual real-time growth rates are calculated as the difference between logarithmic index levels, using index levels published in the same vintage month. For example, from the issue of Economic Trends published in vintage month *t*, index levels for month *t*, *t*-1 and *t*-12 are recorded to calculate growth rates and since they all appear in the same issue, they are all measured according to the same base year. Index levels for months *t*-1 and *t*-12 that are published in vintage month *t* are revised and so represent the most accurate data publicly available at month *t*.

2.3.2.2 Inflation

There may be more than one process through which news of inflation affects stock prices, which may result in conflicting relationships. An unexpected rise in inflation will increase nominal earnings flows to firms. To the extent that pricing is in nominal terms, this would have a positive impact on stock prices. An unexpected jump in inflation may also prompt monetary policy officials to raise nominal interest rates, which will depress stock prices. The mere anticipation by traders of more restrictive policy measures in response to unexpectedly higher inflation may cause stock prices to fall. Higher inflation can also increase the role of depreciation in a firm's tax calculations, thus reducing profits, dividends and stock prices.

In the research that follows, the rate of inflation is measured by the month on month percentage growth rate of the Retail Price Index excluding mortgage payments (RPIX), which was the government's target measure at the time of writing. Monthly RPIX levels were collected from Datastream for the period December 1979 to October 2002 with 1987 as the base year. Even though RPIX levels are never revised by the ONS, there is an important difference between a fully-revised and real-time inflation rate series. RPIX and its associated growth rate for month *t* are released by the ONS midway through month $t+1$. The fully-revised series, conventionally used in empirical research, is represented by ${}_t\pi_n$, which measures the percentage increase in inflation that actually occurred in month t, but which is not made publicly available until month $t+1$ and is later collected in month n. For the real-time series, the inflation rate for vintage month t, ${}_{t-1}\pi_t$, measures the inflation rate publicly announced in month t, but which refers to data collected for the previous month. The real-time series measures the news financial markets would have received, whilst the fully-revised series measures the historical data delayed by one month. This one month lag is far from a trivial matter in the context of risk pricing since the two data vintages represent two very different information sets available to traders.

2.3.2.3 Term Structure of Interest Rates

The discount rate used in the equity pricing formula is determined by two factors: the time value of money and a risk premium. The time value of money is characterised by the term structure of interest rates, which measures the relationship between interest rates and maturity. Specifically it compares the rate at which investors discount cash flows far in the future versus the rate at which investors discount near cash flows. The term structure, denoted as τ_t in the following equation, is measured as the spread between the yields on two risk free assets, long dated government bonds and short dated treasury bills:

$$\tau_t = LGB_t - TB_{t-1}. \tag{2.4}$$

All yields were obtained from Datastream. LGB_t, the long government bond yield series, is the monthly gross yield on 20-year UK gilts. TB_{t-1} measures the mid-percentage discount rate on one month UK Treasury Bills. The yield on one month T-Bills is available from Datastream only at the very end of the month, so to maintain contemporaneity this study follows Fama and Gibbons (1984) and Chen et al. (1986) in calculating the spread using the T-Bill rate that becomes known at the very end of month t-1. Interest rates and yields on bonds are financial time series and are never revised. The term structure measure is therefore a real-time and fully-revised series and is calculated from January 1980 to October 2002. Both assets that make up the series are risk free as the UK government is highly unlikely to default on its debt, so the series isolates term structure effects from any risk associated with the underlying borrower. An unexpected widening of the spread will be caused by higher yields on long dated bonds showing that investors discount farther cash flows more heavily. This will cause the yield curve, a plot of interest rates against maturity, to pivot and become steeper. Heavier discounting of cash flows causes a rise in the discount rate in the equity pricing formula with the resultant cheaper stock prices offering a higher rate of return on equity.

2.3.2.4 Risk Premium

The second determinant of the discount rate is a risk premium, defined as the additional return an investor requires as reward for buying increasing asset risk. When calculated as the internal rate of return in the equity pricing formula, the discount rate is specific to the stock under consideration. It is assumed in APT that asset specific risk can be diversified away in the presence of a sufficient number of assets. For this reason we use instead a systematic risk premium measure that is not asset specific, but designed to capture the premium that investors require as a reward for bearing the non-diversifiable risk of uncertainty in the economy as a whole. In studies of US markets, such as Chen et al. (1986) and Christoffersen et al. (2002), the degree of uncertainty inherent in the economy is measured as the spread of the yield on risky, below investment grade (junk) bonds over the yield on risk free government bonds. This can also be interpreted as a measure of the degree of investor risk aversion. In uncertain economic conditions, the receipt of future payments from low grade debt issuers is more uncertain so yields on junk bonds need to increase to compensate investors for the additional risk they face. Low grade corporations are more likely to default on their coupon payments than the US government and so need to offer higher rates of return to attract investors. Typically the spread of low grade bond yields over government bond yields will be positive and will become wider as economic conditions deteriorate and as investors become more risk averse.

Moody's, Standard and Poor's and Fitch Ratings are the three largest agencies that classify debt issuers in the US according to the risk that they will default on their debt. This classification allows easy identification of high risk bonds, which simplifies the construction of a US measure of a risk premium and makes time series data highly accessible. There are no such comprehensive ratings agencies in the UK, which makes the identification of high risk bonds difficult and the resultant lack of data complicates the construction of a measure of underlying economic uncertainty. An alternative approach follows the method of Poon and Taylor (1991), which uses the spread between the returns on two fixed interest price indices compiled by the Financial Times:

$$PREM_t = r_{FI,t} - r_{GOV,t}, \tag{2.5}$$

where $r_{FI,t}$ and $r_{GOV,t}$ are the returns to the monthly Financial Times Fixed Interest and Government Securities price indices, respectively. Monthly returns are calculated as the difference between consecutive logarithmic monthly price index levels.

There are two problems concerning this measure. First, as the spread between returns to price indices, this variable ignores interest income earned on bonds that is part of their total return. Returns to price indices measure only capital gain and so the spread between the two rates of return is not a true risk premium. Poon and Taylor (1991) overcome this problem by suggesting that the exclusion of interest income may not be crucial to their study because, in the UK, the capital gain contributes a larger proportion than interest income to the total return on fixed interest securities. In the absence of more reliable time series data, the same variables are used here, but it is recognised that they may have some shortcomings.

Second, because of the inverse relationship that exists between the price of bonds and their yield to maturity, the premium measure defined above does not mimic the dynamics of the preferred yield spread variable that US studies have used. In times of economic uncertainty we would expect the spread between the yields on risky and safe assets to widen, the higher return earned on more uncertain assets compensating investors for bearing additional non-diversifiable risk. A rise in yields on riskier assets would make them proportionally cheaper than government securities, causing their price index to fall relatively more than the price index of government securities. The $PREM_t$ measure defined above will be negative in this case and the more uncertain economic conditions are the more negative this measure of capital gain will be.

To differentiate between a true risk premium and a capital gain and to ensure the measure increases with investment uncertainty, this variable is renamed as a capital gain spread, denoted by c_t and constructed in a different way:

$$c_t = r_{GOV,t} - r_{FI,t}, \tag{2.6}$$

where the two returns series are identical to those defined above. Now, the more susceptible debt issuers are to uncertain economic prospects and the more risk averse investors are, the higher will be the yield on risky fixed interest assets relative to safer government securities. The higher the increase in the yields on these risky bonds the larger will be the fall in their price and the more negative will be the return to the Financial Times price index. This will ensure that c_t becomes larger and positive in riskier climates, consistent with the objective of this study to test whether a more uncertain investment climate is rewarded by higher returns in the stock market. For the calculation of the capital gain spread, the government securities price index includes only securities with 15 or more years to maturity. Both indices were obtained from Datastream and cover the period January 1980 to October 2002. Bond yields are never revised and so reflect both real-time and fully-revised data.

2.3.3 Preliminary Statistics

Having explained the construction of each macroeconomic variable, the following tables show preliminary statistics and tests that describe the salient features of their distributions.[10] Panel (A) of Table 2.3.3.1 shows descriptive statistics for the macroeconomic variables. A brief glance at these data can reveal any obvious distributional differences between data vintages. There is a clear difference, for example, between the mean annual growth rates of industrial production for real-time data compared to fully-revised data. Since RPIX is never revised, the only difference between the inflation statistics when measured in real-time and fully-revised vintages is one of timing. The fully-revised series lags one month behind the real-time series so only the first and last observations of the series are different. For this reason, the statistics in Table 2.3.3.1 relating to the two inflation variables are almost identical.

[10] As described in section 2.3.4.2, the econometric procedure used to test APT uses returns on stock portfolios rather than individual stocks. Since the compositions of the portfolios vary over time, descriptive statistics for portfolio returns would be meaningless.

Table 2.3.3.1. Descriptive Statistics for the Raw Macroeconomic Variables.

SERIES	GROWTH RATE	VINTAGE	MEAN	MEDIAN	STANDARD ERROR	SKEWNESS	KURTOSIS	JARQUE-BERA
(A) Raw Series								
${}_{t-i}y_t$	Monthly	RT	0.0002	0.0000	0.0006	-0.0938	**4.0367****	**12.21****
								(0.0022)
${}_ty_n$	Monthly	FR	0.0008	0.0012	0.0006	**-0.3478***	**3.9449****	**15.14****
								(0.0005)
${}_{t-i}y_t$	Annual	RT	0.0056	0.0103	0.0020	**-1.4409****	**6.0037****	**190.60****
								(0.0000)
${}_ty_n$	Annual	FR	0.0106	0.0152	0.0022	**-1.0939****	**5.1859****	**105.21****
								(0.0000)
${}_{t-i}\pi_t$	Monthly	RT	0.0039	0.0034	0.0003	**2.1916****	**12.1174****	**1125.73****
								(0.0000)
${}_t\pi_n$	Monthly	FR	0.0039	0.0034	0.0003	**2.2021****	**12.1542****	**1135.16****
								(0.0000)
τ_t		RT	-0.0009	-0.0007	0.0012	-0.2131	2.4801	**4.97+**
								(0.0833)
c_t		RT	0.0002	-0.0001	0.0009	-0.0635	2.5224	2.69
								(0.2611)
(B) Error Series								
${}_ty_n - {}_{t-i}y_t$	Monthly		0.0006	0.0000	0.0008	**-0.2325+**	**3.5547+**	**5.76***
			(0.5071)					(0.0561)
${}_ty_n - {}_{t-i}y_t$	Annual		**0.0050****	0.0036	0.0014	-0.0963	**5.1038****	**49.09****
			(0.0003)					(0.0000)
${}_t\pi_n - {}_{t-i}\pi_t$	Monthly		0.0000	0.0000	0.0004	-0.0084	**6.3053****	**120.18****
			(0.9621)					(0.0000)

Notes: y, π, τ and c refer to real output, inflation, term structure and capital gain spread variables, respectively. RT and FR denote real-time and fully-revised variables. Panel (A) shows statistics for the raw macroeconomic variables and Panel (B) shows statistics for the error series, measured as the difference between fully-revised and the real-time series. Standard errors are calculated using White (1980) heteroscedasticity consistent covariances. Bracketed values below the mean of the error series are p-values associated with a two-sided test of the null hypothesis that means are equal to zero and hence there is no significant bias in the error conventionally ignored in empirical research. Skewness and kurtosis are tested against null hypotheses of 0 and 3, using asymptotic standard errors of $(6/T)^{1/2}$ and $(24/T)^{1/2}$ respectively. The Jarque-Bera column lists the test statistics for the Jarque Bera test for normality with associated p-values in parentheses. **, * and + indicate statistics that are significant at the 1, 5 and 10% levels respectively. Data are for the period January 1980 to October 2002.

This one month lag is far from a trivial matter in the context of risk pricing since the two data vintages represent two very different information sets available to traders. Since both the term structure and capital gain spread variables are only observed in real-time, there is no fully-revised series to compare their statistics with, but they are included for completeness.

The extent of the error in using fully-revised rather than real-time data is calculated as the difference between the two series for each month of the sample and is shown in Panel (B) of Table 2.3.3.1. Bracketed values below the means of these errors are the probability values associated with two tailed tests of the hypothesis that the mean is equal to zero. A p-value below 0.05 implies rejection of the null hypothesis at the 5% level of significance and a non-zero mean. This test is of particular importance to the errors because non-zero means could imply a significant bias. A significantly positive mean for the error associated with the annual industrial production growth rate, for example, illustrates that the fully-revised data overstate the true information available to traders, which may be due to an upward revision bias. Distributions of the error series are leptokurtic, as shown by the kurtosis statistics in excess of 3 and rejection of the Jarque-Bera normality test.

Time series properties of the variables can be derived from Table 2.3.3.2. The autocorrelation (ACF) and partial autocorrelation functions (PACF) characterise the shape of the correlogram, which shows the degree of serial dependence in the data. ACF's and PACF's that are significantly different from zero show that variables are serially correlated. Ljung-Box (1978) Q statistics and their associated probability values are also listed as a more robust statistical test for serial correlation. The null hypothesis that no autocorrelation exists is emphatically rejected for each of the macroeconomic series.[11] The last of the preliminary tests, whose results are listed in Table 2.3.3.3, shows that all of the macroeconomic series are stationary. This means that first and second order moments of distributions are independent of time. The Augmented Dickey Fuller and Phillips Peron tests use MacKinnon critical values to test for the presence of unit roots in the time series. In Table 2.3.3.3, the null hypothesis that a unit root exists is rejected at the 1% level, which means that the series are all stationary.

[11] The presence of serial correlation presents a serious obstacle to the Ordinary Least Squares (OLS) regression technique, as estimates of coefficient standard errors will be biased which will make standard statistical inference inaccurate. Since coefficient estimates remain unbiased, this does not pose any problems to the econometric techniques employed in this study.

Table 2.3.3.2. Time Series Properties of the Raw Macroeconomic Variables.

	LAG	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
$_{t-i}y_t$	ACF	-0.132*	-0.10	0.07	0.00	0.10	-0.02	-0.02	0.07	0.00	0.01	0.01	0.125*
(monthly)	PACF	-0.132*	-0.12	0.04	0.01	0.12	0.02	0.00	0.05	0.01	0.01	0.00	0.134*
	Q	4.66	7.24	8.64	8.64	11.54	11.60	11.73	12.95	12.95	12.96	12.98	17.34
	PROB	0.03	0.03	0.04	0.07	0.04	0.07	0.11	0.11	0.17	0.23	0.30	0.14
$_ty_n$	ACF	-0.196*	0.043	0.148*	-0.049	0.213*	-0.081	0.003	0.135*	-0.118	0.025	-0.04	-0.023
(monthly)	PACF	-0.196*	0.01	0.163*	0.01	0.206*	-0.03	-0.03	0.08	-0.07	-0.06	-0.06	-0.02
	Q	10.23	10.73	16.60	17.24	29.50	31.28	31.28	36.31	40.12	40.29	40.74	40.88
	PROB	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$_{t-i}y_t$	ACF	0.899*	0.841*	0.771*	0.706*	0.649*	0.568*	0.489*	0.418*	0.346*	0.272*	0.204*	0.14*
(annual)	PACF	0.899*	0.171*	-0.05	-0.03	0.01	-0.143*	-0.09	-0.01	-0.04	-0.07	-0.02	-0.02
	Q	215.67	405.05	565.06	699.61	813.77	901.69	967.05	1014.90	1047.90	1068.30	1079.90	1085.30
	PROB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$_ty_n$	ACF	0.893*	0.834*	0.759*	0.668*	0.601*	0.501*	0.421*	0.339*	0.239*	0.178*	0.115	0.05
(annual)	PACF	0.893*	0.184*	-0.06	-0.152*	0.03	-0.157*	-0.03	-0.04	-0.13*	0.07	0.03	-0.06
	Q	212.70	399.17	554.31	674.71	772.62	841.05	889.49	920.98	936.72	945.53	949.21	949.97
	PROB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$_{t-i}\pi_t$	ACF	0.319*	0.12	0.00	0.05	0.132*	0.259*	0.10	0.02	-0.06	0.08	0.222*	0.73*
	PACF	0.319*	0.02	-0.05	0.07	0.12	0.199*	-0.05	-0.02	-0.06	0.11	0.168*	0.685*
	Q	27.23	31.00	31.01	31.68	36.39	54.59	57.34	57.45	58.48	60.07	73.70	222.08
	PROB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$_t\pi_n$	ACF	0.316*	0.12	-0.01	0.04	0.133*	0.257*	0.10	0.02	-0.06	0.08	0.224*	0.73*
	PACF	0.316*	0.02	-0.05	0.06	0.12	0.196*	-0.06	-0.02	-0.06	0.11	0.169*	0.684*
	Q	26.73	30.40	30.41	30.83	35.63	53.56	56.18	56.30	57.37	58.90	72.78	221.33
	PROB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
τ_t	ACF	0.945*	0.897*	0.847*	0.804*	0.76*	0.712*	0.665*	0.615*	0.573*	0.538*	0.513*	0.48*
	PACF	0.945*	0.03	-0.03	0.03	-0.03	-0.06	-0.02	-0.06	0.04	0.06	0.07	-0.08
	Q	238.67	454.33	647.55	822.11	978.54	1116.50	1237.50	1341.30	1431.50	1511.60	1584.60	1648.80
	PROB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
c_t	ACF	-0.18*	-0.06	-0.15*	-0.07	-0.06	0.23*	-0.10	0.01	-0.08	0.02	0.00	0.10
	PACF	-0.18*	-0.09	-0.184*	-0.149*	-0.148*	0.147*	-0.08	-0.03	-0.07	0.00	0.00	0.04
	Q	8.61	9.45	15.48	16.65	17.55	31.97	34.86	34.91	36.84	36.98	36.98	39.89
	PROB	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: y, π, τ and c refer to real output, inflation, term structure and capital gain spread variables, respectively. *ACF* is the autocorrelation function and *PACF* is the partial autocorrelation function. * indicates a significant correlation function at the 5% level of significance. *Q* statistics are the Ljung-Box (1978) test statistic for serial correlation with *PROB* indicating the p-value associated with a test of the null hypothesis of no serial correlation.

Table 2.3.3.3. Augmented Dickey Fuller and Phillips Peron Tests for Unit Roots in Raw Macroeconomic Variables.

	LAG	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
${}_{t-i}y_t$	ADF	-18.484**	-13.633**	-9.916**	-8.444**	-6.703**	-6.191**	-5.719**	-4.934**	-4.653**	-4.640**	-4.76**	-4.134**	-4.277**
(monthly)	PP	-18.484**	-18.494**	-18.603**	-18.608**	-18.587**	-18.519**	-18.479**	-18.458**	-18.429**	-18.404**	-18.385**	-18.369**	-18.35**
${}_{t}y_n$	ADF	-19.617**	-12.469**	-8.375**	-7.687**	-5.617**	-5.200**	-5.220**	-4.911**	-5.228**	-5.201**	-5.061**	-4.783**	-4.445**
(annual)	PP	-19.617**	-19.622**	-19.572**	-19.439**	-19.371**	-19.297**	-19.274**	-19.265**	-19.266**	-19.273**	-19.281**	-19.288**	-19.295**
${}_{t-i}y_t$	ADF	-3.627**	-2.908*	-3.107*	-2.993*	-2.960*	-3.548**	-3.966**	-4.041**	-4.213**	-4.402**	-4.49**	-4.134**	-4.277**
(monthly)	PP	-3.627**	-3.373*	-3.363*	-3.412*	-3.449*	-3.568**	-3.671**	-3.743**	-3.811**	-3.874**	-3.923**	-3.964**	-3.938**
${}_{t}y_n$	ADF	-3.669**	-2.634+	-2.894*	-3.663**	-3.492**	-4.285**	-4.286**	-4.239**	-4.881**	-4.410**	-4.370**	-4.951**	-3.52**
(annual)	PP	-3.669**	-3.516**	-3.641**	-3.844**	-3.928**	-4.091**	-4.189**	-4.270**	-4.377**	-4.420**	-4.468**	-4.570**	-4.490**
${}_{t-i}\pi_t$	ADF	-11.553**	-9.315**	-8.541**	-7.191**	-7.011**	-5.289**	-5.394**	-5.193**	-4.747**	-4.251**	-3.433*	-3.323*	-3.072*
	PP	-11.553**	-11.531**	-11.565**	-11.52**	-11.494**	-11.513**	-11.656**	-11.777**	-11.879**	-11.915**	-11.957**	-11.987**	-12.249**
${}_{t}\pi_n$	ADF	-11.807**	-9.403**	-8.710**	-8.546**	-6.592**	-5.429**	-5.319**	-4.713**	-4.701**	-3.937**	-3.477**	-3.364*	-2.691+
	PP	-11.807**	-11.78**	-11.793**	-11.701**	-11.655**	-11.651**	-11.755**	-11.850**	-11.928**	-11.951**	-11.979**	-11.999**	-12.228**
τ_t	ADF	-2.704**	-2.583**	-2.630**	-2.546*	-2.586**	-2.705**	-2.731**	-2.794**	-2.676**	-2.473*	-2.275*	-2.390*	-2.489*
	PP	-2.704**	-2.681**	-2.700**	-2.685**	-2.692**	-2.715**	-2.733**	-2.769**	-2.781**	-2.777**	-2.758**	-2.765**	-2.780**
c_t	ADF	-19.364**	-13.485**	-12.470**	-11.441**	-10.763**	-7.560**	-7.404**	-6.841**	-6.678**	-6.134**	-5.725**	-5.114**	-4.118**
	PP	-19.364**	-19.393**	-19.579**	-20.003**	-20.619**	-21.295**	-21.323**	-21.502**	-21.696**	-22.052**	-22.36**	-22.578**	-22.502**

Notes: y, π, τ and c refer to real output, inflation, term structure and capital gain spread variables, respectively. *ADF* and *PP* refer to the Augmented Dickey Fuller and Phillips Peron unit root tests. **, * and + indicate rejection of the null that there exists a unit root in the time series at the 1, 5 and 10% level of significance, respectively, using Mackinnon critical values. A constant term is included in the regressions for real output and inflation variables since they exhibit non-zero means. Time trends are not required for any of the series and sufficient lags are included in the test to account for serial correlation.

As with serially correlated variables, standard inference procedures do not apply to regressions that contain non-stationary variables and so stationarity is a desirable statistical property.

The large magnitude of the errors, especially in the tails of their distributions, and their serial dependence all demonstrate the importance of the consideration of macroeconomic data timing and availability when considering the real-time decision making of stock market operators.

2.3.4 Econometric Method

The econometric approach used here is based on the method introduced by Fama and Macbeth (1973) in their test of CAPM, which was also the foundation of Chen et al.'s (1986) seminal work analysing macroeconomic variables as pervasive risk factors generating stock returns. More recently, Christoffersen et al. (2002) have applied the method to investigate whether real-time and fully-revised data provide different results in US financial studies. The process involves four stages.

2.3.4.1 Stage 1: Expectations Modelling

Assuming that stock markets are semi-strong form efficient, according to Fama's (1970) definition, stock prices will only react to unanticipated news announcements. The first task to perform, therefore, is to extract the part of the new information that is expected and hence already impounded in stock prices from the actual announcement, leaving only the innovations to macroeconomic variables. As an expeditious approach to the modelling of expectations, we follow Christoffersen et al. (2002) in employing two simple models.[12] The first specification employs a rolling constant model of expectations which assumes that investor expectations are constant through time. Differentiating real-time and fully-revised data according to the notation adopted earlier, the estimated expected values of real output and inflation growth are as follows:

[12] A worthy investigation into how best to model economic expectations would require an entirely separate and voluminous work. Instead, we follow the intuitive approach adopted by Christoffersen et al. (2002) to keep this study pertinent to this test of APT, analysing the relative importance of macroeconomic data recorded at different vintages.

$${}_{s+t}\hat{y}_n = \hat{\alpha}^{FR}_{0,y}, \tag{2.7a}$$

$${}_{s+t}\hat{\pi}_n = \hat{\alpha}^{FR}_{0,\pi}, \tag{2.7b}$$

$${}_{s+t-i}\hat{y}_{s+t} = \hat{\alpha}^{RT}_{0,y}, \tag{2.7c}$$

$${}_{s+t-i}\hat{\pi}_{s+t} = \hat{\alpha}^{RT}_{0,\pi}, \tag{2.7d}$$

where y and π denote real output and inflation, respectively; $\hat{\alpha}_0$ is the estimated expected value of real output or inflation growth and is assumed to be constant through time, such that $\hat{y}$ and $\hat{\pi}$ are the fitted values measuring expected real output and inflation growth and the superscripts *FR* and *RT* distinguish coefficients estimated using fully-revised and real-time macroeconomic data. Equations (2.7a) and (2.7b) show expectations models applied to conventional fully-revised macroeconomic data whilst equations (2.7c) and (2.7d) use the more informative real-time formulations. Macroeconomic innovations are calculated as the contemporaneous differences between actual and estimated (expected) values of output and inflation, the latter being provided by equations (2.7a) to (2.7d).[13] These innovations are calculated using a *60*-month estimation window of macroeconomic data that is re-estimated annually as the window is rolled along the sample, where t=1,2,..., 60 refers to a particular month in any given estimation window and s=0, 12, 24, ..., 204 represents the month preceding the next window, demonstrating that the estimation window rolls by 12 months at each iteration[14, 15] This allows expectations to be reformed annually based on five-years of monthly data, rather than the whole sample. Spacing.

The second expectations specification adds a lagged value of the dependent variable to the model, offering a more realistic model of investor expectations where current expectations are dependent on last period's value. The rolling first order autoregressive models of expectations are estimated as:

[13] The practical estimation of these models involves a regression of actual real output growth and inflation growth, for both fully-revised and real-time data, on constants, retaining the residuals as the measures of macroeconomic innovations.

[14] A fixed five-year (60-month) window is chosen to ensure consistent estimates in stage 2, whilst leaving enough remaining observations in the sample to provide a sufficient time series of factor risk prices in stage 3.

[15] To clarify, s=0 for the first estimation window such that expectations are estimated using observations $s+t$=1,2,.....60. For the second estimation window, s=12 such that expectations are re-estimated using observations $s+t$=13, 14, ...72. This window rolls through the sample at 12 month intervals.

$$ {}_{s+t}\widehat{y}_n = \widehat{\rho}^{FR}_{0,y} + \widehat{\rho}^{FR}_{1,y}\left({}_{s+t-1}y_n\right), \tag{2.8a} $$

$$ {}_{s+t}\widehat{\pi}_n = \widehat{\rho}^{FR}_{0,\pi} + \widehat{\rho}^{FR}_{1,\pi}\left({}_{s+t-1}\pi_n\right), \tag{2.8b} $$

$$ {}_{s+t-i}\widehat{y}_{s+t} = \widehat{\rho}^{RT}_{0,y} + \widehat{\rho}^{RT}_{1,y}\left({}_{s+t-i-1}y_{s+t-1}\right), \tag{2.8c} $$

$$ {}_{s+t-i}\widehat{\pi}_{s+t} = \widehat{\rho}^{RT}_{0,\pi} + \widehat{\rho}^{RT}_{1,\pi}\left({}_{s+t-i-1}\pi_{s+t-1}\right), \tag{2.8d} $$

where again y and π denote real output and inflation variables; $\widehat{\rho}_0$ and $\widehat{\rho}_1$ are the sample estimates of the intercept and autoregressive coefficients, such that $\widehat{y}$ and $\widehat{\pi}$ are the fitted values measuring expected real output and inflation growth and the superscripts FR and RT distinguish coefficients estimated using fully-revised and real-time macroeconomic data. Equations (2.8a) and (2.8b) show expectations models applied to conventional fully-revised macroeconomic data. These assume that traders predict the fully-revised measure of activity for month $s+t$ based on the fully-revised measure for month $s+t-1$, both of which cannot be observed until long after month $s+t$. If matched with returns in month $s+t$, this fully-revised specification implies that trades take place on the basis of information that is not yet available. Equations (2.8c) and (2.8d) are more pertinent real-time formulations that assume traders anticipate preliminary releases of output and inflation because these form the basis of their real-time information set and hence asset valuations. These are based explicitly on information available to traders at time $s+t$ and are therefore contemporaneous with returns for month $s+t$. Consistent with equations (2.7a) to (2.7d), innovations are calculated using a *60*-month estimation window of macroeconomic data that is rolled along the sample allowing expectations to be re-estimated annually.

As an interesting extension, this analysis also employs an AR(1) model where the lagged value of the series is the latest revision to the macroeconomic variable, rather than simply last period's real-time observation:

$$ {}_{s+t-i}\widetilde{y}_{s+t} = \widetilde{\rho}^{RT}_{0,y} + \widetilde{\rho}^{RT}_{1,y}\left({}_{s+t-i-1}y_{s+t}\right), \tag{2.8e} $$

$$ {}_{s+t-i}\widetilde{\pi}_{s+t} = \widetilde{\rho}^{RT}_{0,\pi} + \widetilde{\rho}^{RT}_{1,\pi}\left({}_{s+t-i-1}\pi_{s+t}\right), \tag{2.8f} $$

with $\tilde{\rho}_0$ and $\tilde{\rho}_1$ representing the sample estimates of the intercept and autoregressive coefficients such that $\tilde{y}$ and $\tilde{\pi}$ are the fitted values measuring expected real output and inflation growth, thus differentiating this model of expectations from the orthodox AR(1) estimated in equations (2.8c) and (2.8d). This approach assumes traders adjust their expectations to revisions once they become available in month $s+t$ and isolates the unanticipated informational content of the new data released.[16] As the difference between rates of return, the capital gain spread measure already reflects innovations and thus does not require expectations modelling.[17]

Simple time series models (equations 2.7 and 2.8) are estimated to generate measures of innovations to the macroeconomic variables. Although more complicated time series models could be applied for modelling expectations, the models are kept simple deliberately so as not to distract from the central theme of this chapter, the comparison of sources of macroeconomic data when applied to this particular asset pricing test. Indeed, by following the Box Jenkins method, a simple AR(1) model is found to perform very well against more sophisticated alternatives in describing the time series properties of the data.

2.3.4.2 Stage 2: Factor Sensitivities

The APT suggests that asset returns are generated by more than one common factor and this is expressed algebraically in the multifactor model of equation (2.1). Using time series data on UK stock returns and UK macroeconomic innovations as the systematic risk factors in the multifactor returns generating model expressed in equation (2.1), the sensitivity of stock returns to the unanticipated risk factors are estimated. Returns to individual stocks, however, are known to be very noisy and measurement error in estimates of the factor sensitivities is minimized by grouping stocks into portfolios and estimating the sensitivity of portfolio returns, $r_{p,s+t}$, to the

[16] As an alternative expectation model and in order to appraise further the sensitivity of our empirical results to the choice of expectations model, vector autoregressive (VAR) expectation models are also considered. Further details of results obtained using VAR expectations are shown in section 2.5.

[17] Other ways of calculating expected inflation beyond a simple time series approach have been considered, but are not applied due to lack of statistical properties or information content. Fama and Gibbons (1984) base their measure on the Fisher Hypothesis, but the data used in this work do not replicate the statistical properties their method requires. Blake et al. (2002) propose a measure of unexpected inflation based on the term structure of interest rates, but find "evidence that the information content in yield curve data is not robust." Blake et al. (2002), p.830.

systematic risk factors.[18] As Fama and MacBeth (1973) state: "Estimates of b_i for portfolios are indeed more precise than those for individual securities." The informational loss incurred by grouping is outweighed by the benefit of reducing measurement error when using portfolio rather than individual stock returns. To maximise the spread of the returns across portfolios and therefore to estimate more precisely the explanatory power of the risk factors, stocks are ranked by their total market value (size) and then grouped into twenty equally weighted portfolios.[19] Market values of each stock at the beginning of each year of the sample are obtained from Datastream. Firm size is related to stock returns according to empirical studies (Banz (1981), for example) and it is hoped that forming portfolios on the basis of size will produce the desired spread in portfolio returns without inducing bias into tests of the macroeconomic variables. It is important to note, however, that this is based on empirical regularity rather than theoretical foundations.

Following Fama and Macbeth (1973), let N be the number of stocks to be allocated into portfolios at the beginning of the sample and let $int(N/20)$ be the largest integer equal to or less than $N/20$. Twenty portfolios are formed on the basis of firm size and the middle 18 portfolios each has $int(N/20)$ securities. If N is even, the first and last portfolios each have $int(N/20) + 1/2\ [N - 20int(N/20)]$, whilst the last portfolio with the largest firms gets an extra security if N is odd. Returns to portfolios are calculated as an equally weighted average of the returns to their constituent securities. The sample begins in January 1980, so portfolios are initially formed based on the market values of firms at the very end of 1979. Monthly portfolio returns are calculated for the following 12 months. Portfolios are reformed at the end of each year in the sample and monthly returns for the subsequent year are

[18] Shanken (1992) presents a consistent estimator for an asymptotic covariance matrix for the estimation of factor sensitivities which eliminates measurement error. Unfortunately, the adjustment cannot be applied to rolling estimates of the sensitivities.

[19] This portfolio approach was also used by Black et al. (1972) in their famous test of CAPM as it allows aggregation of data on a large number of securities in an efficient manner. Although the choice of the number of portfolios is arbitrary, samples in which the number of securities entering each group is large will yield estimated factor sensitivities in stage 2 that are virtually free of sampling error and will provide consistent and more precise estimates of factor risk prices in stage 3. Applying this test to appropriately large portfolios rather than the underlying securities will virtually eliminate the measurement error problem. In tests of CAPM, Black et al. (1972) use 10 portfolios, whilst Fama and MacBeth (1973) use 20. To maintain comparability with other tests of APT we follow Chen et al. (1986) and Poon and Taylor (1991) in using 20 portfolios, whilst Christoffersen et al. (2002) use a 25 portfolio data set provided by Kenneth French. Stocks in each portfolio are equally weighted to avoid introducing selection bias into the procedure that would bias the estimation of factor risk sensitivities. Given the time-varying composition of the stock portfolios, summary statistics for the portfolio data are not included.

recalculated. This allows for the delisting, death or new issue of stocks, as well as changes in firm market values and therefore the movement of securities between portfolios.

The sensitivities of portfolio returns to macroeconomic risk factors are estimated for each portfolio as follows:

$$r_{p,s+t} = \beta^{FR}_{0,p,w} + \beta^{FR}_{y,p,w}\left({}_{s+t}y_n - {}_{s+t}\hat{y}_n\right) + \beta^{FR}_{\pi,p,w}\left({}_{s+t}\pi_n - {}_{s+t}\hat{\pi}_n\right) + \beta^{FR}_{c,p,w}\left({}_{s+t-i}c_{s+t}\right) + u^{FR}_{p,s+t}, \tag{2.9a}$$

$$r_{p,s+t} = \beta^{RT}_{0,p,w} + \beta^{RT}_{y,p,w}\left({}_{s+t-i}y_{s+t} - {}_{s+t-i}\hat{y}_{s+t}\right) + \beta^{RT}_{\pi,p,w}\left({}_{s+t-i}\pi_{s+t} - {}_{s+t-i}\hat{\pi}_{s+t}\right) + \beta^{RT}_{c,p,w}\left({}_{s+t-i}c_{s+t}\right) + u^{RT}_{p,s+t}, \tag{2.9b}$$

$$r_{p,s+t} = \beta^{RTL}_{0,p,w} + \beta^{RTL}_{y,p,w}\left({}_{s+t-i}y_{s+t} - {}_{s+t-i}\tilde{y}_{s+t}\right) + \beta^{RTL}_{\pi,p,w}\left({}_{s+t-i}\pi_{s+t} - {}_{s+t-i}\tilde{\pi}_{s+t}\right) + \beta^{RTL}_{c,p,w}\left({}_{s+t-i}c_{s+t}\right) + u^{RTL}_{p,s+t}, \tag{2.9c}$$

where $r_{p,s+t}$ represent portfolio returns; p=1,2,.....20 refers to each portfolio; y and π are real output and inflation as defined earlier and c represents the capital gain spread defined in Section 2.3.2.4; $u^{FR}_{p,s+t}$, $u^{RT}_{p,s+t}$ and $u^{RTL}_{p,s+t}$ are error terms; *FR* and *RT* superscripts denote the use of fully-revised and real-time macroeconomic data and *RTL* shows the use of real-time data, but where AR(1) expectations are formed using the latest revision to the macroeconomic series as the lagged value. The coefficients of each equation measure the sensitivity of stock portfolio returns to the respective risk factors (or 'factor sensitivities'). These are estimated using a fixed 60-month estimation window that is rolled through the sample by 12 month intervals, with t and s defined as above, while w=1,2,..., 18 references the estimates to each window in order to emphasize that the factor sensitivities are re-estimated annually, so allowing them to vary over time.[20] Similar to (2.7a), (2.7b), (2.8a) and (2.8b), equation (2.9a) utilizes fully-revised macroeconomic data implying that returns for month $s+t$ are determined by information not available to traders until long after this month. Specification (2.9b) estimates factor sensitivities using real-time data, thus matching returns in month $s+t$ to macroeconomic information publicly available in

[20] To reiterate, s=0 for the first estimation window (w=1) such that factor sensitivities are estimated using observations $s+t$=1, 2...60. For the second estimation window (w=2), s=12 such that factor sensitivities are re-estimated using observations $s+t$=13, 14 ...72. The window is of fixed length (60 months) and rolls through the sample by 12 months at each iteration.

month $s+t$. Finally, (2.9c) differentiates the AR(1) expectations models described in (2.8e) and (2.8f) from the orthodox AR(1) identified in (2.8c) and (2.8d) for real-time data.

The term structure of interest rates and the capital gain spread variables use the returns on long-term government bonds in their construction. In anticipation of collinearity between the two variables and following the empirical evidence of Chen et al. (1986) and Christoffersen et al. (2002), they are not used in the same equation in initial tests; rather, only the capital gain spread uncertainty measure is used, since, by its construction, it is likely to pick up some term structure effects as well as economic uncertainty. As shown in equations (2.9a) to (2.9c), the capital gain spread is a financial variable meaning that it already measures innovations and can only be observed in real-time.

In their study using real-time US data, Christoffersen et al. (2002) also estimate variations of equations (2.9a) to (2.9c) to include the annual percentage growth rate of real activity. They follow Chen et al. (1986) in arguing that stock returns reflect expectations of future growth far into the future. To capture this relationship they choose to regress current returns on growth rates one period ahead. By leading the real activity variables, both studies relate stock returns to information that traders do not yet possess and ignore the informational flow from real activity news announcements to stock prices. To maintain a strictly real-time framework, focusing on the arrival of information that forces traders to adjust their expectations of future growth, stock returns are regressed only on information that was available to traders. For completeness, and to test whether shocks to the annual and monthly growth rates of industrial production affect stock returns symmetrically, the same variations of the multifactor model that Christoffersen et al. (2002) employ are estimated.

The sample period includes two major stock market crashes in October and November 1987 and September 2001 that were not caused by any of the macroeconomic factors used in this study. In real-time, stock market participants are unable to anticipate such crashes and so they are included in the sample to maintain a strict ex-ante approach to the test. A very simple, ex post, approach in a retrospective study would employ three dummy variables, taking values of unity in the months of October and November 1987 and September 2001 and zero otherwise, to ensure coefficient estimates reflect only the sensitivity of returns to the defined risk factors.

The robustness of the empirical findings to the inclusion of these intercept dummies is discussed and analysed in section 2.5.

2.3.4.3 Stage 3: Market Price of Risk Factors

Using the condition that no arbitrage opportunities exist, Ross (1976) derives a linear pricing rule for expected asset returns, expressed in equation (2.2). In the third stage of the procedure this pricing rule is estimated using factor sensitivities estimated by equations (2.9a)-(2.9c). For each of the 12 months immediately following an estimation window, the market price of risk is estimated by cross-section across portfolio returns:

$$r_{p,s+j} = \lambda^{FR}_{0,s+j} + \lambda^{FR}_{y,s+j}\hat{\beta}^{FR}_{y,p,w} + \lambda^{FR}_{\pi,s+j}\hat{\beta}^{FR}_{\pi,p,w} + \lambda^{FR}_{c,s+j}\hat{\beta}^{FR}_{c,p,w} + \varepsilon^{FR}_{p,s+j}, \qquad (2.10a)$$

$$r_{p,s+j} = \lambda^{RT}_{0,s+j} + \lambda^{RT}_{y,s+j}\hat{\beta}^{RT}_{y,p,w} + \lambda^{RT}_{\pi,s+j}\hat{\beta}^{RT}_{\pi,p,w} + \lambda^{RT}_{c,s+j}\hat{\beta}^{RT}_{c,p,w} + \varepsilon^{RT}_{p,s+j}, \qquad (2.10b)$$

$$r_{p,s+j} = \lambda^{RTL}_{0,s+j} + \lambda^{RTL}_{y,s+j}\hat{\beta}^{RTL}_{y,p,w} + \lambda^{RTL}_{\pi,s+j}\hat{\beta}^{RTL}_{\pi,p,w} + \lambda^{RTL}_{c,s+j}\hat{\beta}^{RTL}_{c,p,w} + \varepsilon^{RTL}_{p,s+j}, \qquad (2.10c)$$

where $\varepsilon^{FR}_{p,s+j}$, $\varepsilon^{RT}_{p,s+j}$ and $\varepsilon^{RTL}_{p,s+j}$ denote error terms, j=61,62,...,72 such that $s+j$=61,62,...,274 indicates that this cross-section regression (across p) is performed sequentially in each of the *12* months following each estimation window.[21] This generates time series of estimates of the market prices of risk, $\hat{\lambda}^{FR}_{k,s+j}$, $\hat{\lambda}^{RT}_{k,s+j}$ and $\hat{\lambda}^{RTL}_{k,s+j}$ (for k=y, π or c), using the corresponding time varying factor sensitivities, $\hat{\beta}^{FR}_{k,p,w}$, $\hat{\beta}^{RT}_{k,p,w}$ and $\hat{\beta}^{RTL}_{k,p,w}$, obtained from each estimation window.[22] Intuitively, the $\hat{\beta}^{FR}_{k,p,w}$, $\hat{\beta}^{RT}_{k,p,w}$ and $\hat{\beta}^{RTL}_{k,p,w}$ coefficient estimates measure the sensitivity of portfolio returns to each macroeconomic risk factor, quantifying the degree of risk faced by investors, whilst the $\hat{\lambda}^{FR}_{k,s+j}$, $\hat{\lambda}^{RT}_{k,s+j}$ and $\hat{\lambda}^{RTL}_{k,s+j}$ estimates quantify the market price of this risk and

[21] To clarify, the first estimation window (t=1, 2... 60) generates a set of estimated factor sensitivities for each portfolio. In each of the 12 months following this window ($s+j$=61, 62... 72*)*, portfolio returns are regressed, by cross-section on these estimated factor sensitivities to generate the market price of the risk factor. As this cross-section regression (across the twenty portfolios) is performed in each month $s+j$, this step generates a time series of 12 estimates of prices of risk for each risk factor. Factor sensitivities are assumed to remain constant for these 12 months, before they are re-estimated in the second estimation window, but they vary across portfolios in each month.

[22] Since no inference is drawn from these estimated factor sensitivities, serial correlation in the innovations does not pose a problem for this econometric procedure as estimated factor sensitivities retained from stage 2 are unbiased.

their respective products, $\hat{\lambda}^{FR}_{k,s+j}\hat{\beta}^{FR}_{k,p,w}$, $\hat{\lambda}^{RT}_{k,s+j}\hat{\beta}^{RT}_{k,p,w}$ and $\hat{\lambda}^{RTL}_{k,s+j}\hat{\beta}^{RTL}_{k,p,w}$, show the risk premium or excess expected return earned by investors as reward for bearing idiosyncratic risk. Thus, a significantly positive estimate of the market price implies that a portfolio whose returns are positively correlated with macroeconomic innovations will be rewarded in the stock market by a higher expected return. This would also indicate that these risk factors predict expected stock returns. Descriptive statistics and time series plots of the market prices for risk are reported in section 2.4.

2.3.4.4 Stage 4: Significance Tests

In the fourth stage, the time series of estimated market prices of risk are regressed on a constant:

$$\hat{\lambda}^{FR}_{k,s+j} = \mu^{FR}_{k} + \eta^{FR}_{k,s+j}, \tag{2.11a}$$

$$\hat{\lambda}^{RT}_{k,s+j} = \mu^{RT}_{k} + \eta^{RT}_{k,s+j}, \tag{2.11b}$$

$$\hat{\lambda}^{RTL}_{k,s+j} = \mu^{RTL}_{k} + \eta^{RTL}_{k,s+j}, \tag{2.11c}$$

with $k=y,\ \pi\ or\ c$ again denoting the macroeconomic factor under consideration; $\eta^{FR}_{k,s+j}$, $\eta^{RT}_{k,s+j}$ and $\eta^{RTL}_{k,s+j}$ denote error terms, and the estimated values $\hat{\mu}^{FR}_{k}$, $\hat{\mu}^{RT}_{k}$ and $\hat{\mu}^{RTL}_{k}$ are the time series average market prices of risk for each macroeconomic risk factor, which are tested for statistical significance by a two tailed *t*-test using White (1980) heteroscedasticity consistent standard errors and covariances.[23] In addition, in order to evaluate the statistical significance of any difference between average prices of risk measured using real-time and fully-revised data, two further tests are performed. Firstly, a Wald *F*-test on equations (2.11b) and (2.11c) using real-time data under the restriction that the coefficient estimate is equal to the average price of risk for the factor measured using the fully-revised data in (2.11a), where test significance implies a statistically significant difference between the average prices of risk in the two datasets. Secondly, the equality of means between fully-revised and real-time prices of risk is tested using a two-sample *t*-test, assuming unequal

[23] Since the order of the estimated prices of risk do not matter to the calculation of the mean, any autocorrelation may be removed from the series by re-ordering it so it is sufficient to use heteroscedasticity consistent covariances.

variances between the samples, against the one sided alternative that the real-time average is greater than the fully-revised average.

2.4 EMPIRICAL RESULTS

Following the four-stage econometric procedure set out in Section 2.3.4, time series of the market prices of risk for the three pervasive macroeconomic factors are generated from January 1985 to October 2002. To test whether shocks to the annual and monthly growth rates of real output affect stock returns symmetrically, we estimate three versions of each equation in stage 2. The first includes the monthly growth rate of real output, the second includes the annual growth rate of real output and the third specification uses both monthly and annual growth rates.[24] Tables 2.4.1 and 2.4.2 report the time series averages, White (1980) heteroscedasticity consistent standard errors and *t* statistics of the estimated market prices of risk for the three pervasive macroeconomic factors measured using fully-revised and real-time data respectively. The results are presented in distinct panels representing different expectations models. The crucial and powerful result, irrespective of expectations, is the clear difference between the statistics for fully-revised and real-time data. None of the average market prices of risk are significantly different from zero using fully-revised data, as shown in Table 2.4.1, implying that the economic variables do not represent systematic risk factors that are rewarded in the stock market. That is, economic factors are not important for the pricing of stocks, and the APT appears to be redundant.

Conversely, unanticipated inflation is a significantly priced factor at the 10% level and economic uncertainty, measured by the capital gain spread, is statistically significant at the 5% level when using real-time data, as shown by Table 2.4.2. This pricing relationship is slightly stronger when using autoregressive expectations, with more coefficients on the inflation surprise variable significant across alternative specifications and larger *t*-statistics on the capital gain spread variable.

[24] This follows the procedure of Christoffersen et al. (2002) and Chen et al. (1986) who argue that stock returns reflect expectations of future growth far into the future. To capture this relationship they regress current returns on growth rates one period ahead. By leading the real activity variables, these studies relate stock returns to information that traders do not yet possess and ignore the informational flow from real activity news announcements to stock prices. To maintain a strictly real-time framework, focusing on the arrival of information that forces traders to adjust their expectations of future growth, stock returns are regressed only on information that was available to traders.

Table 2.4.1. Average Estimated Market Prices of Risk for Fully-Revised Macroeconomic Factors.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Constant Expectations					
Average price of risk	0.0014	-0.0012		0.0001	0.0031
Standard error	0.0015	0.0019		0.0007	0.0026
	(0.9640)	(-0.6090)		(0.1027)	(1.2040)
Average price of risk	0.0019		-0.0012	-0.0003	0.0033
Standard error	0.0015		0.0044	0.0007	0.0024
	(1.2622)		(-0.2842)	(-0.3708)	(1.3482)
Average price of risk	0.0018	-0.0013	-0.0038	-0.0003	0.0029
Standard error	0.0015	0.0019	0.0047	0.0007	0.0026
	(1.1668)	(-0.6874)	(-0.8039)	(-0.3491)	(1.1172)
(B) AR(1) Expectations					
Average price of risk	0.0020	-0.0019		-0.0004	0.0034
Standard error	0.0015	0.0020		0.0007	0.0025
	(1.3528)	(-0.9536)		(-0.4922)	(1.3375)
Average price of risk	0.0020		-0.0036	-0.0003	0.0032
Standard error	0.0014		0.0025	0.0007	0.0023
	(1.3899)		(-1.4275)	(-0.4091)	(1.3621)
Average price of risk	0.0021	-0.0021	-0.0036	-0.0006	0.0031
Standard error	0.0015	0.0021	0.0027	0.0007	0.0024
	(1.3825)	(-1.0053)	(-1.3203)	(-0.8641)	(1.2937)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities. Risk factors are measured using fully-revised macroeconomic variables. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero.

Table 2.4.2. Average Estimated Market Prices of Risk for Real-Time Macroeconomic Factors.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Constant Expectations					
Average price of risk	0.0015	-0.0015		**0.0020***	**0.0042+**
Standard error	0.0015	0.0018		0.0009	0.0023
	(0.9891)	(-0.8529)		(2.1248)	(1.8329)
Average price of risk	0.0015		-0.0028	0.0015	**0.0043+**
Standard error	0.0014		0.0042	0.0009	0.0023
	(1.0171)		(-0.6784)	(1.6225)	(1.8431)
Average price of risk	0.0013	-0.0004	-0.0032	0.0014	0.0036
Standard error	0.0015	0.0017	0.0043	0.0009	0.0024
	(0.9084)	(-0.2231)	(-0.7584)	(1.4909)	(1.5172)
(B) AR(1) Expectations					
Average price of risk	0.0013	-0.0016		**0.0017+**	**0.0042+**
Standard error	0.0015	0.0017		0.0009	0.0023
	(0.9211)	(-0.9707)		(1.9401)	(1.8551)
Average price of risk	0.0013		-0.0022	0.0013	**0.0048***
Standard error	0.0015		0.0024	0.0009	0.0022
	(0.8928)		(-0.8810)	(1.5185)	(2.1973)
Average price of risk	0.0012	-0.0007	-0.0023	**0.0015+**	**0.0045***
Standard error	0.0015	0.0016	0.0026	0.0009	0.0022
	(0.7646)	(-0.4504)	(-0.8959)	(1.7195)	(2.0292)
(C) AR(1) Expectations with fully-revised lagged variable					
Average price of risk	0.0014	-0.0019		**0.0016+**	**0.0045+**
Standard error	0.0015	0.0017		0.0009	0.0023
	(0.9777)	(-1.1551)		(1.7771)	(1.9406)
Average price of risk	0.0013		-0.0030	0.0013	**0.0043+**
Standard error	0.0014		0.0040	0.0009	0.0023
	(0.9434)		(-0.7384)	(1.4751)	(1.8721)
Average price of risk	0.0017	-0.0001	-0.0040	0.0014	0.0037
Standard error	0.0014	0.0017	0.0042	0.0009	0.0023
	(1.1601)	(-0.0752)	(-0.9719)	(1.5468)	(1.5655)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities. Risk factors are measured using real-time macroeconomic variables. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero.

These findings are in direct contrast to those of Christoffersen et al. (2002) who find that, under their realistic expectations models, unanticipated inflation is significantly priced only for fully-revised data, whilst their credit risk premium is not significantly priced at the 5% level for either data vintage.

Concerning the signs of these coefficients, a positive market price for surprise inflation implies that stocks whose returns are positively correlated with inflation news are more valuable than stocks whose correlation between returns and inflation news is negative. An inflationary shock reduces the real value of fixed income assets whose cash flows are fixed in nominal terms. As a hedge against this risk, investors would want to hold equity that offers positive returns when inflation unexpectedly rises. Stocks that demonstrate this positive correlation should therefore be valued more highly in the stock market. Inflation shocks also help to predict future expected stock returns.

The capital gain spread also has a positive market price that is significantly different from zero. This relationship strengthens when more realistic autoregressive expectations are used and when annual output shocks are included in the multifactor model. A positive price suggests that the stock market values stocks with a positive correlation between returns and economic uncertainty more highly than stocks whose returns fall in riskier climates. Economic uncertainty is a non-diversifiable risk that is rewarded in the stock market and when measured as a capital gain spread can help to predict future stock returns. Industrial production shocks, however, are never significantly priced. This is not to say that real output surprises are not correlated with stock returns, rather that the market does not view such shocks as risk factors that should affect the expected return on equity. This may reflect the declining role of the manufacturing sector in the UK economy and the higher number of service sector stocks listed on the Financial Times Stock Exchange.

Panel C of Table 2.4.2 uses AR(1) expectations defined by equations (2.8e) and (2.8f), where the latest and most informative revision to the macroeconomic variable is used as the lagged value of the series, rather than simply last period's real-time observation. This specification assumes that traders take notice of the first revision to economic variables at the time of data releases, which can only be measured in real-time. The pattern of the results is broadly similar in that inflation shocks and uncertainty are positively priced factors, indicating that the arrival of macroeconomic news announcements can be separated into two distinct categories:

the revision to last period's announcement and new information. By using the revision to last period's announcement, this model of expectations isolates the new information as the risk factor influencing stock returns. Extracting the impact of data revisions, however, weakens the pricing relationships, showing that data revisions make up an important part of macroeconomic news releases. Perhaps more realistically, announcements of the revision and the new data release typically occur in quick succession, giving very little time for stock prices to change to reflect the two stages of information arrival. More likely, prices adjust after the entire data announcement and in response to both the data revision and the new information, which is the relationship captured by the orthodox AR(1) model of expectations.

Table 2.4.3 presents further comparison of the difference between the average prices of risk for real-time compared to fully-revised data. The Wald test restricts the coefficient in equation (2.11) to be the average price of risk measured using fully-revised data. This restriction is rejected at the 10% level for unanticipated inflation across all expectations models and output specifications and at the 5% level for more than half of the tests, indicating that the average price of risk is statistically different between real-time and fully-revised data. A one-sided test of the equality of means of the two samples presented in Table 2.4.3 provides further evidence at the 10% level when rolling constant expectations models are used and at the more stringent 5% level for the two rolling AR(1) expectations models that the mean for real-time data is significantly greater than the mean for fully-revised data for unanticipated inflation. There is no statistical evidence to support any difference in the mean price of risk between data vintages for the other factors, even though the average price of risk for the capital gain spread is significantly different from zero for real-time data, but not for fully-revised data. This may be explained by the fact that the capital gain spread measure can only be measured in real-time and so the variable is identical in both fully-revised and real-time data vintages. Despite the lack of statistical evidence to support a significant difference between real-time and fully-revised pricing, the economic and statistical contributions of this variable as a predictor of stock returns become apparent when the other risk factors of the returns generating process are measured using real-time data. This is shown in Table 2.4.2 by the significance of the average price of economic uncertainty at the 5% level.

Table 2.4.3. Hypothesis Tests on the Average Prices of Risk.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Constant Expectations					
Wald Coeff. Restriction	0.0012	0.0273		**4.0671***	0.2230
	(0.9719)	(0.8689)		(0.0450)	(0.6373)
Equality of Mean	0.0245	-0.1213		**1.6223+**	0.3146
	(0.4901)	(0.4518)		(0.0528)	(0.3766)
Wald Coeff. Restriction	0.1005		0.1537	**3.8068+**	0.1832
	(0.7516)		(0.6955)	(0.0524)	(0.6691)
Equality of Mean	-0.2118		-0.2653	**1.4942+**	0.3042
	(0.4162)		(0.3954)	(0.0680)	(0.3806)
Wald Coeff. Restriction	0.1123	0.2615	0.0163	**3.3042+**	0.0833
	(0.7379)	(0.6096)	(0.8985)	(0.0705)	(0.7731)
Equality of Mean	-0.2248	0.3545	0.0798	**1.3819+**	0.2072
	(0.4111)	(0.3616)	(0.4682)	(0.0839)	(0.4180)
(B) AR(1) Expectations					
Wald Coeff. Restriction	0.2014	0.0319		**5.7514***	0.1222
	(0.6541)	(0.8584)		(0.0173)	(0.7270)
Equality of Mean	-0.3092	0.1069		**1.8196***	0.2499
	(0.3787)	(0.4575)		(0.0349)	(0.4014)
Wald Coeff. Restriction	0.2004		0.3457	**3.4501+**	0.5317
	(0.6549)		(0.5572)	(0.0646)	(0.4667)
Equality of Mean	-0.3090		0.4133	**1.4424+**	0.4985
	(0.3787)		(0.3398)	(0.0750)	(0.3092)
Wald Coeff. Restriction	0.4054	0.6794	0.2587	**5.7579***	0.3849
	(0.5250)	(0.4107)	(0.6116)	(0.0173)	(0.5357)
Equality of Mean	-0.4405	0.5034	0.3491	**1.8835***	0.4274
	(0.3299)	(0.3075)	(0.3636)	(0.0302)	(0.3347)
(C) AR(1) Expectations with fully-revised lagged variable					
Wald Coeff. Restriction	0.1532	0.0001		**4.9322***	0.2342
	(0.6959)	(0.9920)		(0.0274)	(0.6289)
Equality of Mean	-0.2688	-0.0143		**1.7039***	0.3455
	(0.3941)	(0.4943)		(0.0446)	(0.3650)
Wald Coeff. Restriction	0.2242		0.0234	**3.2949+**	0.2448
	(0.6364)		(0.8785)	(0.0709)	(0.6213)
Equality of Mean	-0.3181		0.1330	**1.4077+**	0.3502
	(0.3753)		(0.4472)	(0.0800)	(0.3632)
Wald Coeff. Restriction	0.0930	1.3101	0.0109	**4.9991***	0.0563
	(0.7606	(0.2536)	(0.9170)	(0.0264)	(0.8126)
Equality of Mean	-0.2015	0.7229	-0.0866	**1.7465***	0.1723
	(0.4202)	(0.2351)	(0.4655)	(0.0407)	(0.4317)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The Wald test of coefficient restrictions tests the null hypothesis that the average price of risk for real-time macroeconomic risk factors is not significantly different from its fully-revised counterpart. *F*-statistics are reported along with *p*-values in parentheses associated with the two-sided alternative hypothesis. The equality of mean *t*-statistic tests the null hypothesis that the average price of risk for real-time factors is not significantly greater than its fully-revised counterpart. The *p*-values reported in parentheses are associated with the one-sided alternative and assume unequal variances between samples. **, * and + indicate test statistics that are significant at the 1, 5 and 10% levels respectively.

Tables 2.4.4 to 2.4.6 display summary statistics for the market prices of risk, calculated by equation (2.10) in the third stage of the econometric methodology explained above, with each table representing different expectations assumptions. Table 2.4.4 uses rolling constant expectations models in stage 1, whilst Table 2.4.5 employs a rolling AR(1) and Table 2.4.6 utilises a rolling AR(1) where the lagged value of the expectations model measures the most informative revision concerning the macroeconomic variables. Each table compares the market prices of risk calculated using fully-revised data with those calculated using real-time data in order to uncover simple distributional discrepancies between the different data vintages.

Examination of Tables 2.4.4 to 2.4.6 reveals a very clear difference between the mean and median price of unanticipated inflation risk for fully-revised compared to real-time macroeconomic variables. Both measures are much larger for real-time data than fully-revised data for this risk factor. This feature holds across all output specifications and particularly for the two rolling AR(1) expectations models as shown in Tables 2.4.5 and 2.4.6. Similar patterns in the measures of location are found for the capital gain spread measure, although the differences between data vintages are less pronounced, as confirmed by the explicit hypotheses tests displayed in Table 2.4.3. This may not be surprising given that the capital gain spread, as a financial variable, is measured identically in fully-revised and real-time data vintages. However, it is important to emphasise that the average price of economic uncertainty, captured by the capital gain spread, is significantly different from zero in more cases and at a more stringent significance level than the average price of unanticipated inflation risk, but only when all other variables in the returns generating process are measured using real-time data. Following the discussion of Tables 2.4.2 and 2.4.3, this shows that the economic and statistical contributions of this risk factor to the prediction of stock returns only become apparent when using real-time data.

Market prices of macroeconomic risk factors measured using fully-revised data are skewed to the left with, skewness statistics often significantly different from zero when tested using asymptotic standard errors. Market prices calculated using real-time macroeconomic data are skewed to the right, but these measures are not often statistically different from zero.

Table 2.4.4. Summary Statistics for Market Prices of Risk Assuming Rolling Constant Expectations.

	Constant		**Monthly Industrial Production**		**Annual Industrial Production**		**Inflation**		**Capital Gain Spread**	
	FR	*RT*	*FR*	*RT*	*FR*	*RT*	*FR*	*RT*	*FR*	*RT*
M	0.0014	0.0015	-0.0012	-0.0015			0.0001	**0.0020***	0.0031	**0.0042+**
Med	0.0024	0.0020	0.0029	-0.0013			0.0007	0.0013	0.0024	0.0043
SD	0.0213	0.0215	0.0282	0.0255			0.0104	0.0135	0.0376	0.0333
S	-0.478	**-0.199+**	**-0.363***	0.127			**-0.507****	0.214	-0.225	0.085
K	**7.034****	**7.550****	**6.361****	**4.467****			**3.946****	**3.906****	**4.561****	**3.532+**
J-B	**153.27****	**186.04****	**105.45****	**19.77****			**17.13****	**8.95***	**23.53****	2.79
M	0.0019	0.0015			-0.0012	-0.0028	-0.0003	0.0015	0.0033	**0.0043+**
Med	0.0020	0.0009			-0.0070	-0.0012	0.0000	0.0016	0.0041	0.0049
SD	0.0219	0.0208			0.0638	0.0613	0.0108	0.0134	0.0355	0.0341
S	-0.098	-0.111			0.365*	0.207	**-0.366***	0.229	-0.087	0.171
K	**6.994****	**8.934****			**4.768****	**5.849****	**3.978****	**3.448+**	**4.028****	**3.840****
J-B	**142.56****	**314.36****			**32.61****	**73.88****	**13.31****	**3.66**	**9.70****	**7.34***
M	0.0018	0.0013	-0.0013	-0.0004	-0.0038	-0.0032	-0.0003	0.0014	0.0029	0.0036
Med	0.0023	0.0021	0.0028	-0.0026	-0.0054	-0.0021	0.0007	0.0016	0.0025	0.0050
SD	0.0224	0.0212	0.0283	0.0256	0.0684	0.0627	0.0108	0.0134	0.0375	0.0345
S	0.092	-0.187	**-0.451****	0.025	-0.105	**0.332***	**-0.498****	0.233	**-0.397***	0.040
K	**7.398****	**8.359****	**6.546****	**4.907****	**5.175****	**6.277****	**3.843****	**3.491+**	**4.831****	**3.685***
J-B	**172.76****	**257.32****	**119.36****	**32.46****	**42.58****	**99.71****	**15.19****	**4.092**	**35.52****	4.24

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The table reports summary statistics for the time series of market prices of risk when macroeconomic factors are measured using fully-revised (*FR*) and real-time (*RT*) data and when expectations are measured using a rolling constant model. Sample mean (*M*), median (*Med*), standard deviation (*SD*), skewness (*S*), kurtosis (*K*) and the Jarque-Bera (*J-B*) normality test statistic are calculated. **, *, + indicate statistics that are statistically significant at the 1, 5 and 10% level of significance. The null hypotheses that sample means are equal to zero are tested against the two-sided alternative using White (1980) heteroscedasticity consistent standard errors. Skewness is tested against the null of zero and Kurtosis against the null of 3 using asymptotic standard errors of $(6/T)^{1/2}$ and $(24/T)^{1/2}$ respectively. Jarque-Bera statistics test the null that distributions are normal.

Table 2.4.5. Summary Statistics for Market Prices of Risk Assuming Rolling AR(1) Expectations.

	Constant		Monthly Industrial Production		Annual Industrial Production		Inflation		Capital Gain Spread	
	FR	*RT*	*FR*	*RT*	*FR*	*RT*	*FR*	*RT*	*FR*	*RT*
M	0.0020	0.0013	-0.0019	-0.0016			-0.0004	**0.0017+**	0.0034	**0.0042+**
Med	0.0026	0.0018	0.0024	-0.0016			0.0008	0.0011	0.0034	0.0036
SD	0.0215	0.0214	0.0288	0.0242			0.0103	0.0128	0.0366	0.0330
S	**-0.458****	-0.202	**-0.309+**	0.254			**-0.548****	0.098	-0.127	0.143
K	**6.866****	**7.595****	**7.160****	**4.573****			**4.076****	**3.665***	**4.138****	3.334
J-B	**140.75****	**189.74****	**157.73****	**24.37****			**21.06****	4.29	**12.12****	1.73
M	0.0020	0.0013			-0.0036	-0.0022	-0.0003	0.0013	0.0032	**0.0048***
Med	0.0022	0.0012			-0.0041	-0.0016	0.0003	0.0014	0.0022	0.0059
SD	0.0207	0.0218			0.0371	0.0359	0.0103	0.0129	0.0343	0.0319
S	-0.246	-0.227			**-0.500****	-0.056	-0.207	0.205	0.076	0.208
K	**7.927****	**7.325****			**4.852****	**4.394****	**5.043****	**4.034****	**4.299****	**3.660***
J-B	**218.57****	**168.67****			**39.50****	**17.43****	**38.74****	**11.02****	**15.26****	**5.47+**
M	0.0021	0.0012	-0.0021	-0.0007	-0.0036	-0.0023	-0.0006	**0.0015+**	0.0031	**0.0045***
Med	0.0021	0.0023	0.0016	-0.0012	-0.0025	-0.0016	-0.0003	0.0009	0.0024	0.0047
SD	0.0220	0.0219	0.0301	0.0241	0.0399	0.0375	0.0103	0.0129	0.0348	0.0322
S	-0.233	**-0.286+**	**-0.447****	0.264	-0.274	**-0.430***	**-0.511****	**0.297+**	-0.040	0.207
K	**6.684****	**6.594****	**8.002****	**4.798****	**5.608****	**6.299****	**4.485****	**4.201****	**3.774***	**3.493+**
J-B	**122.96****	**118.08****	**230.18****	**31.32****	**63.34****	**103.62****	**28.96****	**16.00****	**5.40+**	3.70

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The table reports summary statistics for the time series of market prices of risk when macroeconomic factors are measured using fully-revised (*FR*) and real-time (*RT*) data and when expectations are measured using a rolling AR(1) model. Sample mean (*M*), median (*Med*), standard deviation (*SD*), skewness (*S*), kurtosis (*K*) and the Jarque-Bera (*J-B*) normality test statistic are calculated. **, *, + indicate statistics that are statistically significant at the 1, 5 and 10% level of significance. The null hypotheses that sample means are equal to zero are tested against the two-sided alternative using White (1980) heteroscedasticity consistent standard errors. Skewness is tested against the null of zero and Kurtosis against the null of 3 using asymptotic standard errors of $(6/T)^{1/2}$ and $(24/T)^{1/2}$ respectively. Jarque-Bera statistics test the null that distributions are normal.

Table 2.4.6. Summary Statistics for Market Prices of Risk Assuming Rolling AR(1) Expectations Where Lagged Values are the Most Recent Revision.

	Constant		Monthly Industrial Production		Annual Industrial Production		Inflation		Capital Gain Spread	
	FR	*RT*	*FR*	*RT*	*FR*	*RT*	*FR*	*RT*	*FR*	*RT*
M	0.0020	0.0014	-0.0019	-0.0019			-0.0004	**0.0016+**	0.0034	**0.0045+**
Med	0.0026	0.0020	0.0024	-0.0018			0.0008	0.0010	0.0034	0.0042
SD	0.0215	0.0214	0.0288	0.0243			0.0103	0.0132	0.0366	0.0341
S	**-0.458****	-0.236	**-0.309+**	**0.435****			**-0.548****	**0.325+**	-0.127	0.079
K	**6.866****	**7.569****	**7.160****	**4.932****			**4.076****	**3.888****	**4.138****	3.285
J-B	**140.75****	**188.17****	**157.73****	**40.04****			**21.06****	**10.80****	**12.12****	0.94
M	0.0020	0.0013			-0.0036	-0.0030	-0.0003	0.0013	0.0032	**0.0043+**
Med	0.0022	0.0010			-0.0041	0.0003	0.0003	0.0015	0.0022	0.0044
SD	0.0207	0.0207			0.0371	0.0591	0.0103	0.0129	0.0343	0.0340
S	-0.246	-0.142			**-0.500****	0.061	-0.207	0.170	0.076	0.186
K	**7.927****	**8.601****			**4.852****	**4.973****	**5.043****	3.350	**4.299****	**3.776***
J-B	**218.57****	**280.43****			**39.50****	**34.85****	**38.74****	2.12	**15.26****	**6.61***
M	0.0021	0.0017	-0.0021	-0.0001	-0.0036	-0.0040	-0.0006	0.0014	0.0031	0.0037
Med	0.0021	0.0025	0.0016	-0.0007	-0.0025	-0.0009	-0.0003	0.0012	0.0024	0.0052
SD	0.0220	0.0210	0.0301	0.0252	0.0399	0.0607	0.0103	0.0127	0.0348	0.0342
S	-0.233	-0.152	**-0.447****	**0.528****	-0.274	0.084	**-0.511****	0.167	-0.040	0.037
K	**6.684****	**8.358****	**8.002****	**5.793****	**5.608****	**5.119****	**4.485****	**3.440+**	**3.774***	**3.568***
J-B	**122.96****	**256.76****	**230.18****	**79.53****	**63.34****	**40.29****	**28.96****	2.712	**5.40+**	2.92

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The table reports summary statistics for the time series of market prices of risk when macroeconomic factors are measured using fully-revised (*FR*) and real-time (*RT*) data and when expectations are measured using a rolling AR(1) model, where the lagged value of the dependent variable is the fully-revised and therefore most informative measure available. Sample mean (*M*), median (*Med*), standard deviation (*SD*), skewness (*S*), kurtosis (*K*) and the Jarque-Bera (*J-B*) normality test statistic are calculated. **, *, + indicate statistics that are statistically significant at the 1, 5 and 10% level of significance. The null hypotheses that sample means are equal to zero are tested against the two-sided alternative using White (1980) heteroscedasticity consistent standard errors. Skewness is tested against the null of zero and Kurtosis against the null of 3 using asymptotic standard errors of $(6/T)^{1/2}$ and $(24/T)^{1/2}$ respectively. Jarque-Bera statistics test the null that distributions are normal.

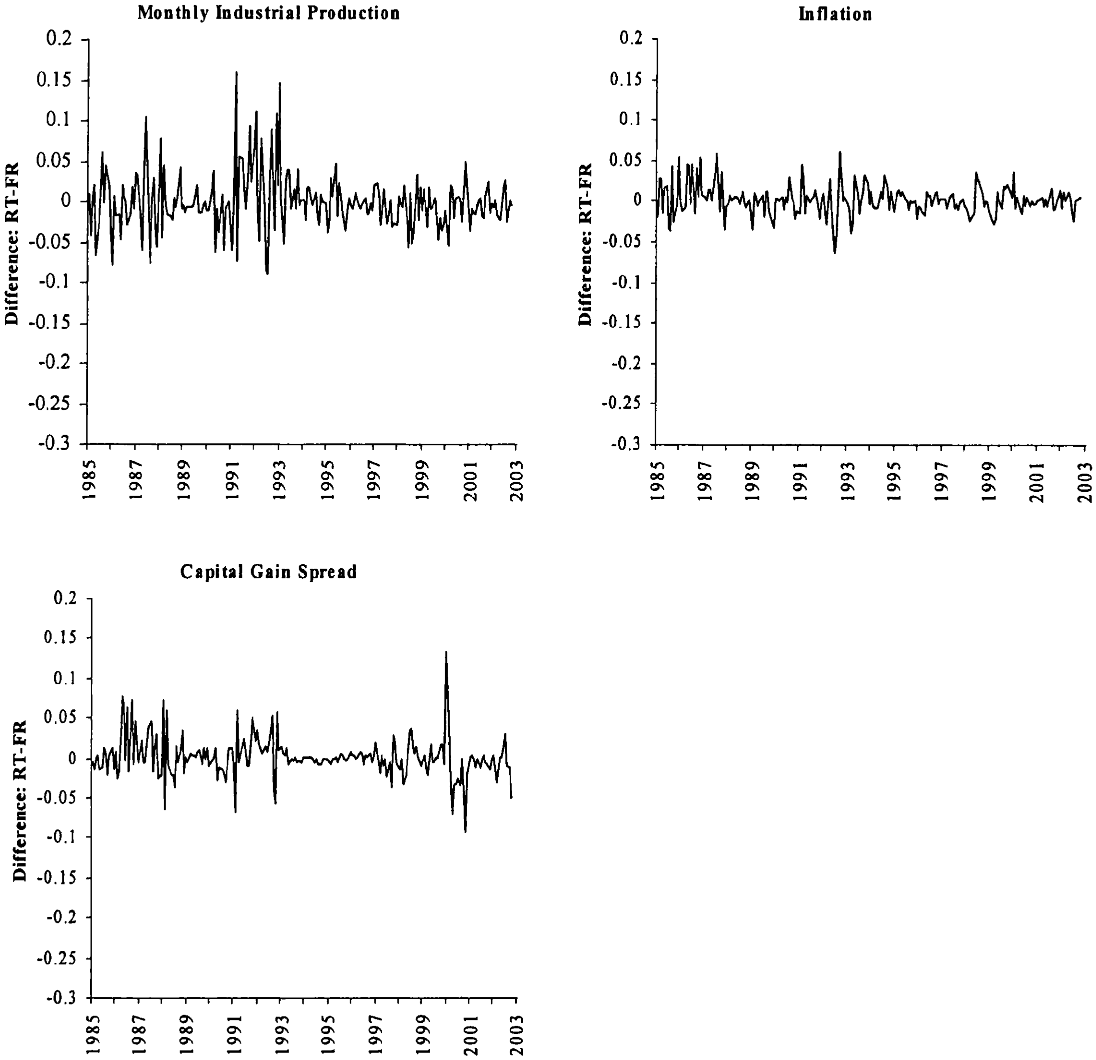
Market prices of risk are leptokurtic for each macroeconomic variable and for both fully-revised and real-time data, which, together with the skewness measures, cause rejection of the null hypothesis that distributions are normally distributed under the Jarque-Bera test for normality. Distributions of the market prices of risk for factors measured using real-time data are located further to the right relative to the distributions for factors measured using fully-revised data, and for the unanticipated inflation and economic uncertainty risk factors in particular, implying that they contain more observations in the right hand tails. This gives strong support to the difference in risk pricing between data vintages identified in Tables 2.4.1 to 2.4.3 and emphasises the importance of the measurement, selection and treatment of macroeconomic variables when included in empirical financial studies.

Finally, Figures 2.4.1 to 2.4.9 show time series plots of the difference between real-time and fully-revised market prices of risk. For clarity, the plots show the difference between real-time and fully-revised prices rather than both series on the same graph. The plots show that there are many months with large pricing differentials, indicating episodes of severe discrepancy between risk pricing using real-time rather than fully-revised data. The positive spikes are generally larger than the negative ones and there are clear periods where real-time prices are persistently above fully-revised prices, specifically during the early 1990's for monthly industrial production growth, the late 1980's for inflation shocks, and both these periods for the capital gain spread. These distinct intervals also reveal more volatile differences between the risk prices for each data vintage and correspond to particularly vigorous macroeconomic business cycle fluctuations, suggesting the need to investigate asymmetric pricing relationships.

2.5 ROBUSTNESS CHECKS

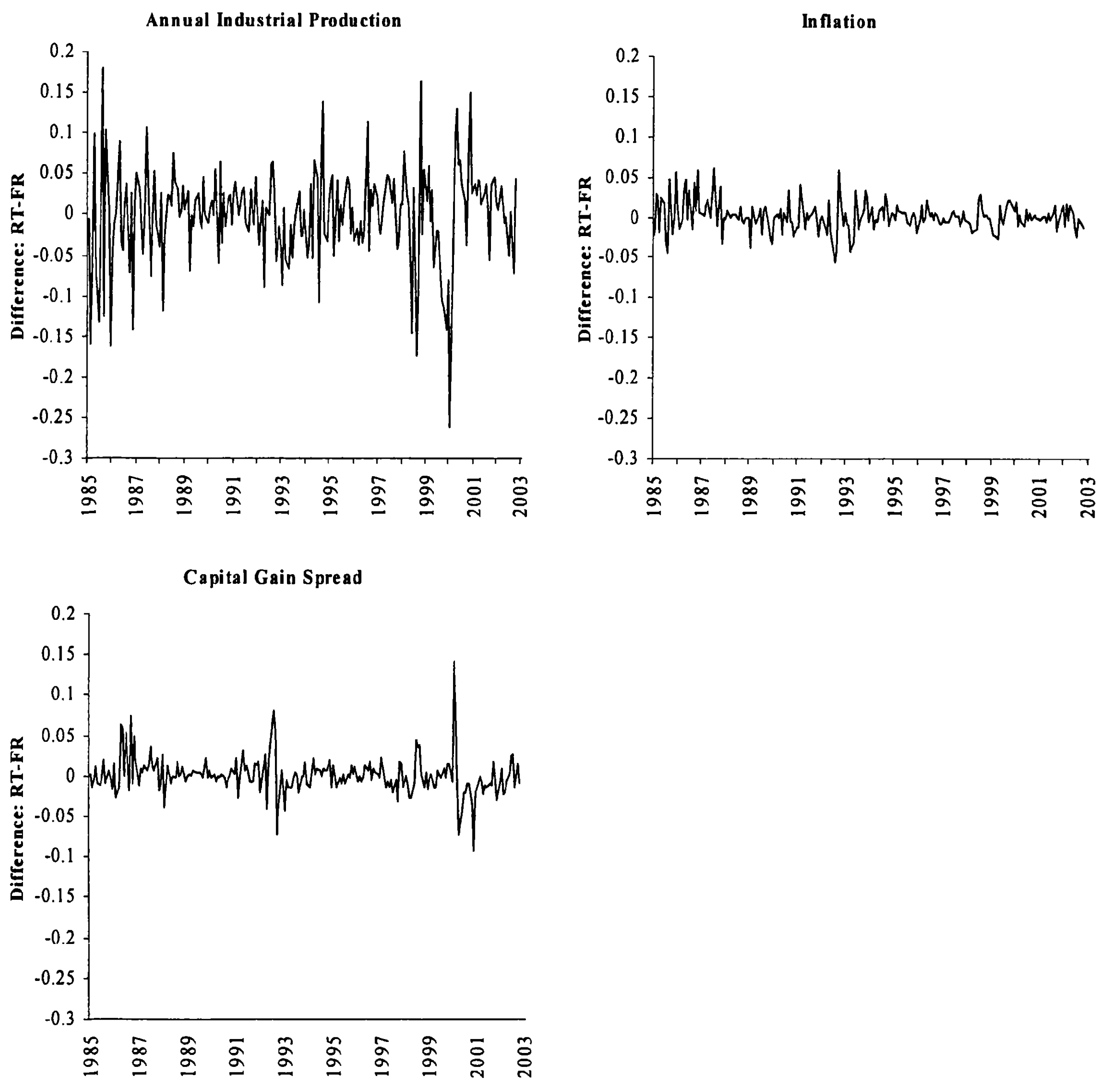
This section presents alternative approaches to the econometric methodology described in section 2.3.4 to ensure that the findings presented in section 2.4 are robust. First, simple dummy variables are added to the returns generating model, estimated in stage 2, to examine the effect on risk pricing of data outliers caused by stock market crashes of October and November 1987 and September 2001. Second, a term structure of interest rates variable is included in stage 2 estimations (with dummy variables excluded to allow comparison with results displayed in section 2.4) to test its pricing influence and contribution to the prediction of stock returns.

Figure 2.4.1.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling Constant Expectations and Including Monthly Industrial Production Growth Innovations Only.



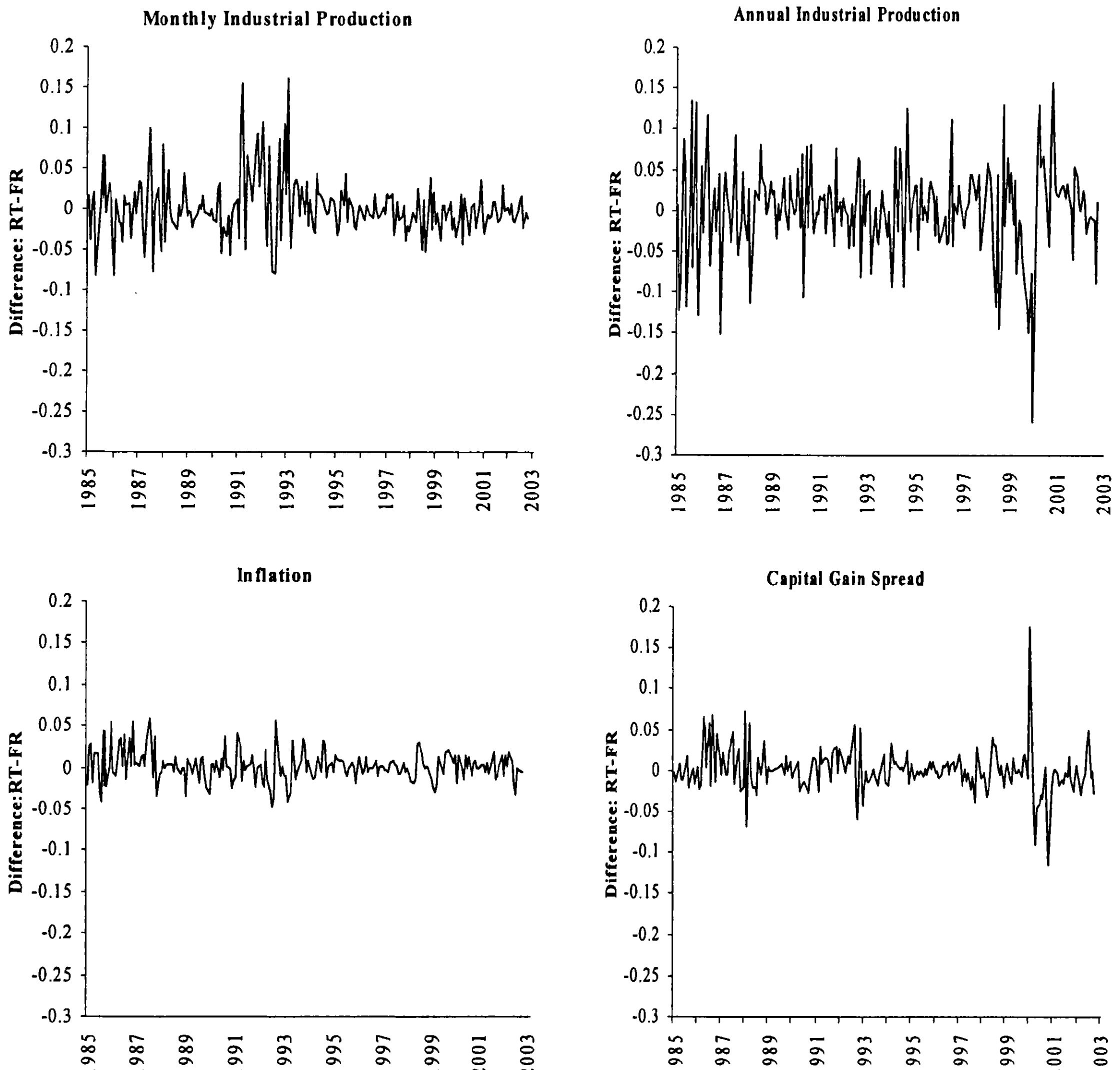
Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling constant models. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes only monthly industrial production growth.

Figure 2.4.2.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling Constant Expectations and Including Annual Industrial Production Growth Innovations Only.



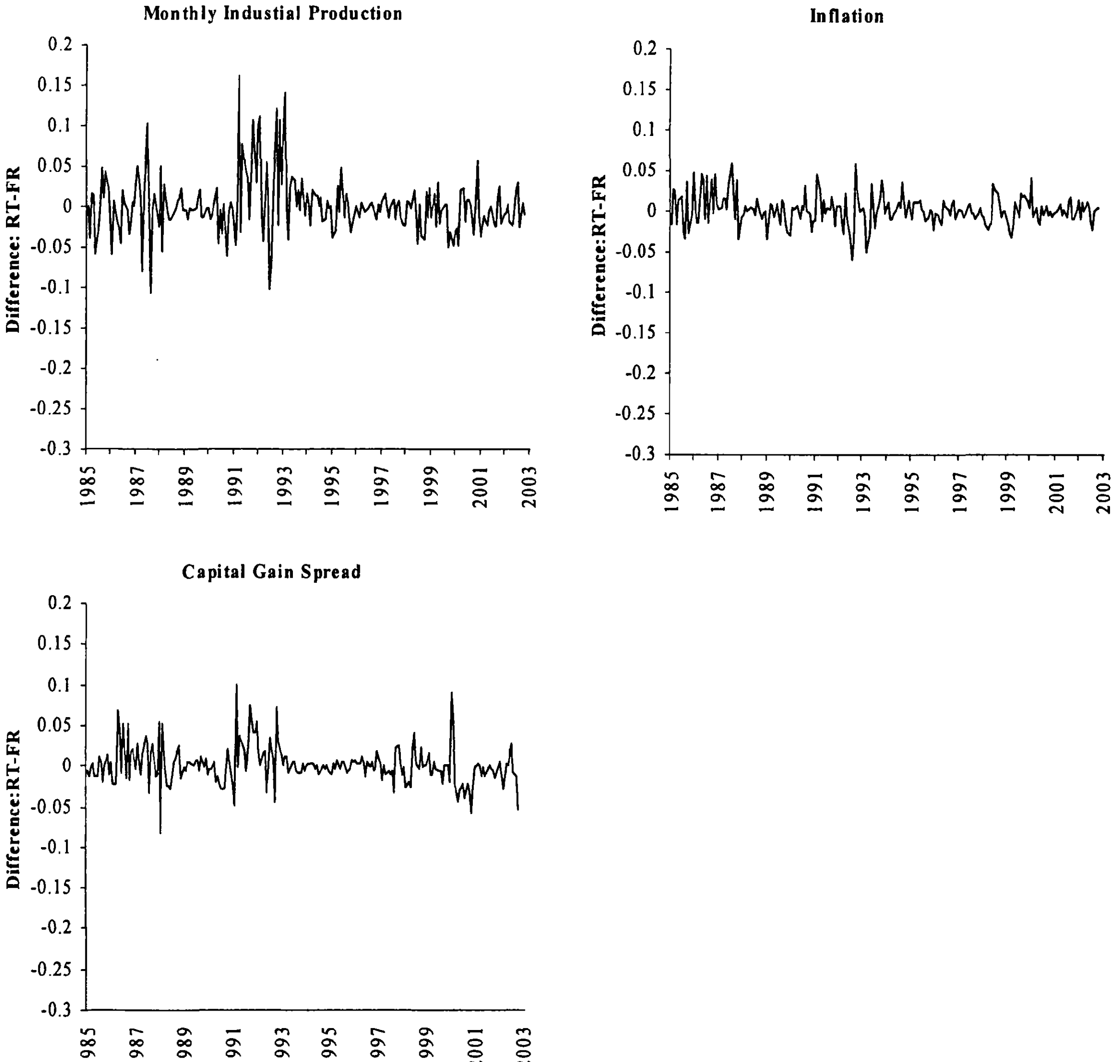
Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling constant models. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes only annual industrial production growth.

Figure 2.4.3.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling Constant Expectations and Including Monthly and Annual Industrial Production Innovations.



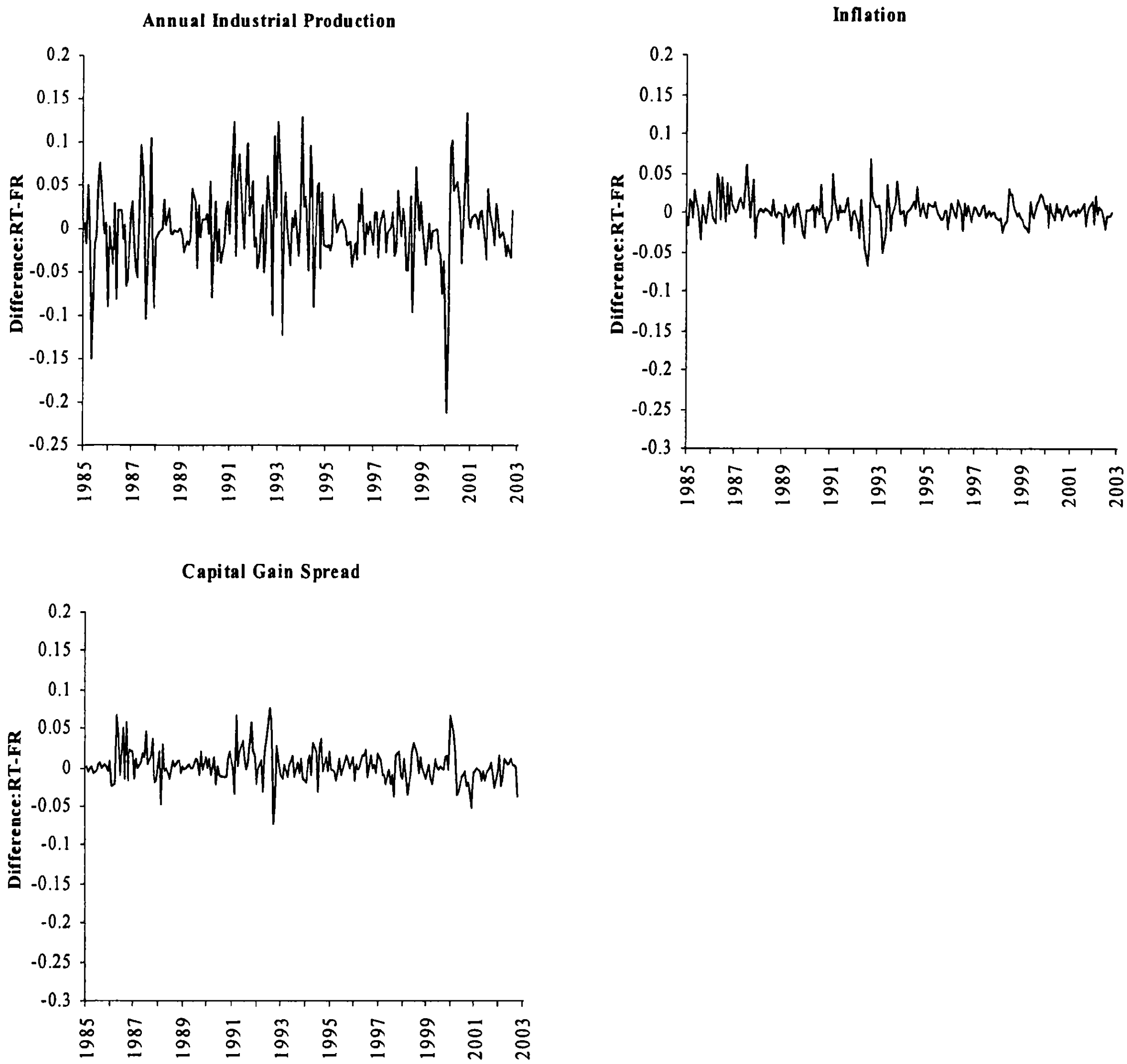
Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling constant models. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes both monthly and annual industrial production growth.

Figure 2.4.4.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling AR(1) Expectations and Including Monthly Industrial Production Growth Innovations Only.



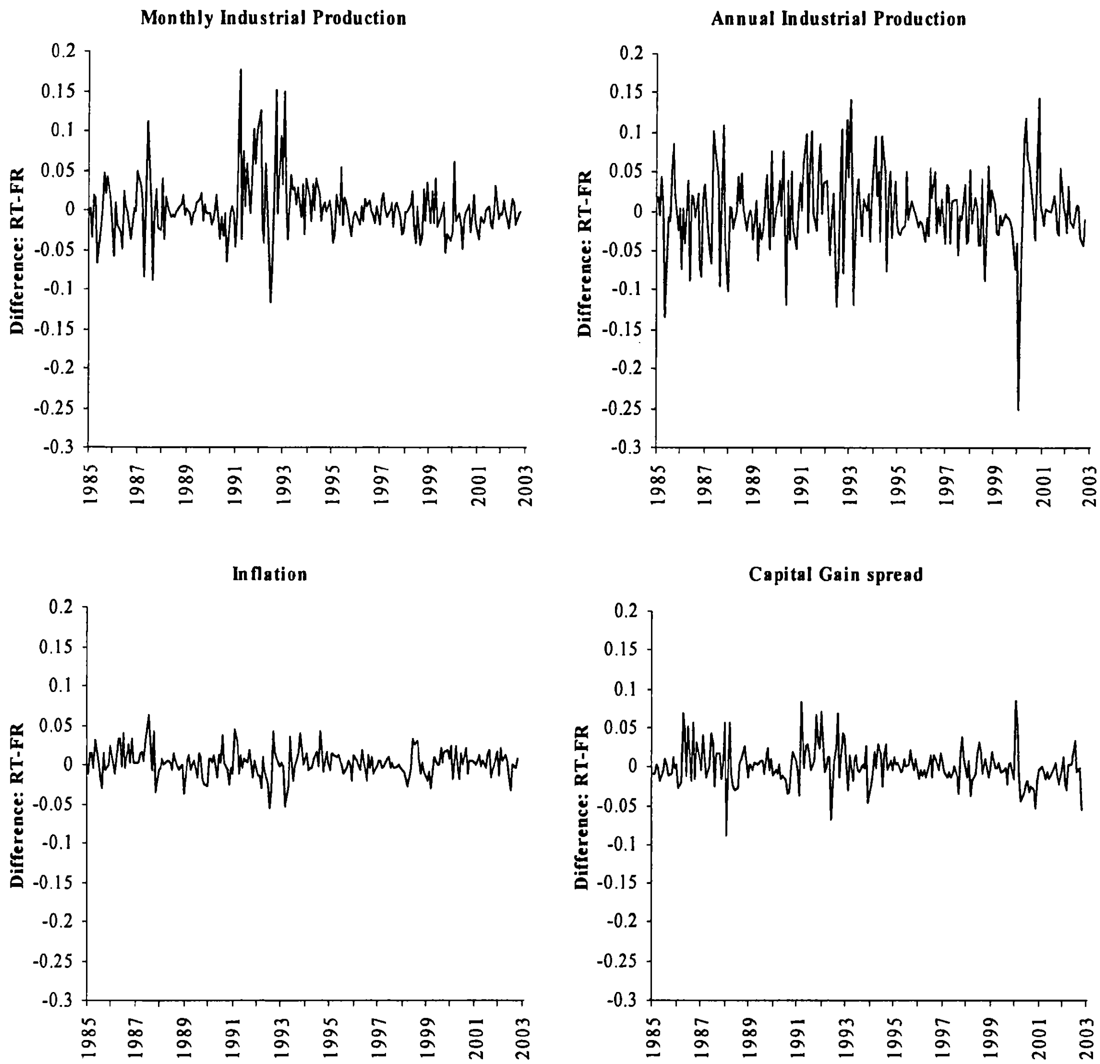
Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling AR(1) models. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes only monthly industrial production growth.

Figure 2.4.5.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling AR(1) Expectations and Including Annual Industrial Production Growth Innovations Only.



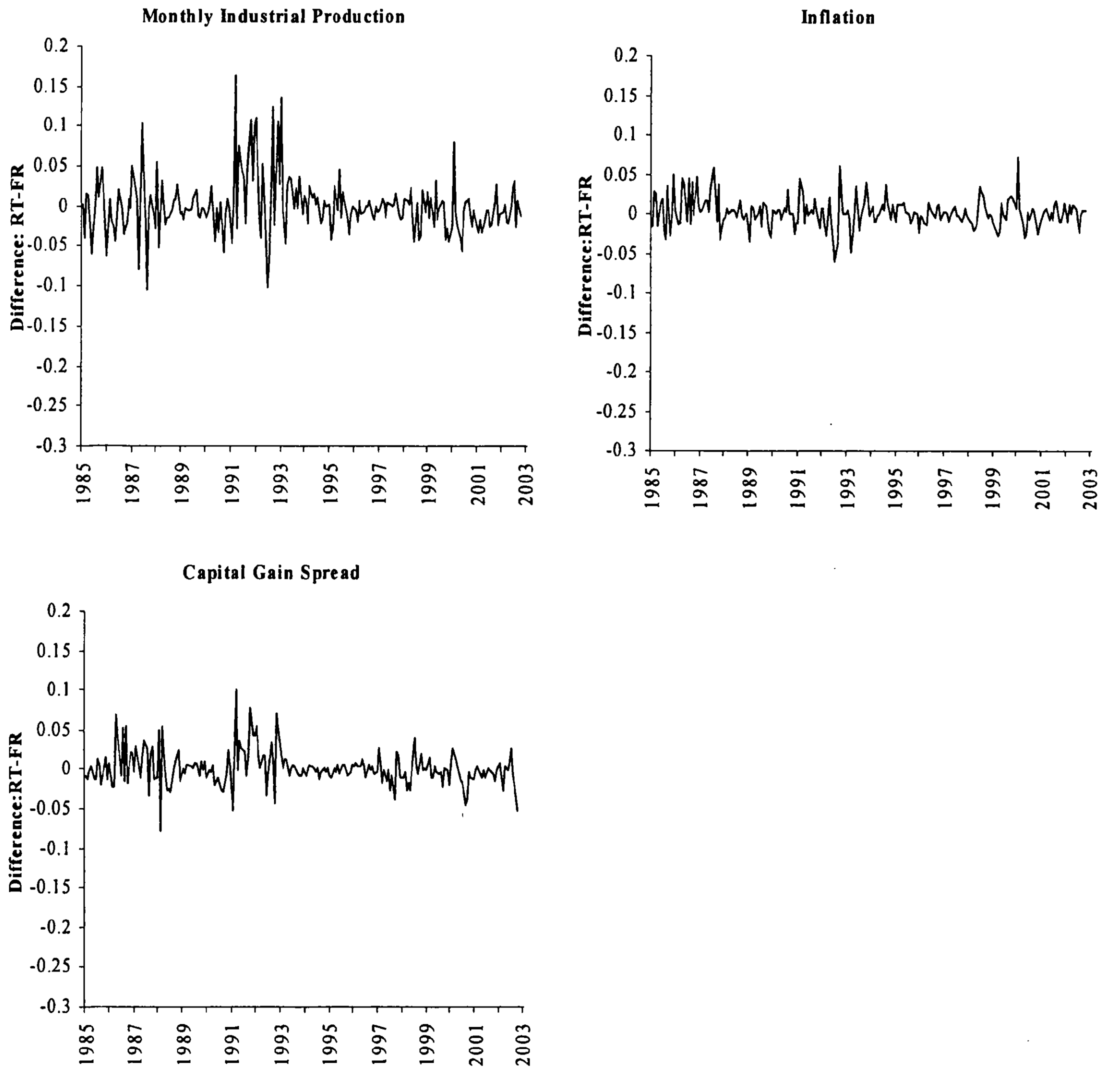
Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling AR(1) models. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes only annual industrial production growth.

Figure 2.4.6.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling AR(1) Expectations and Including Monthly and Annual Industrial Production Innovations.



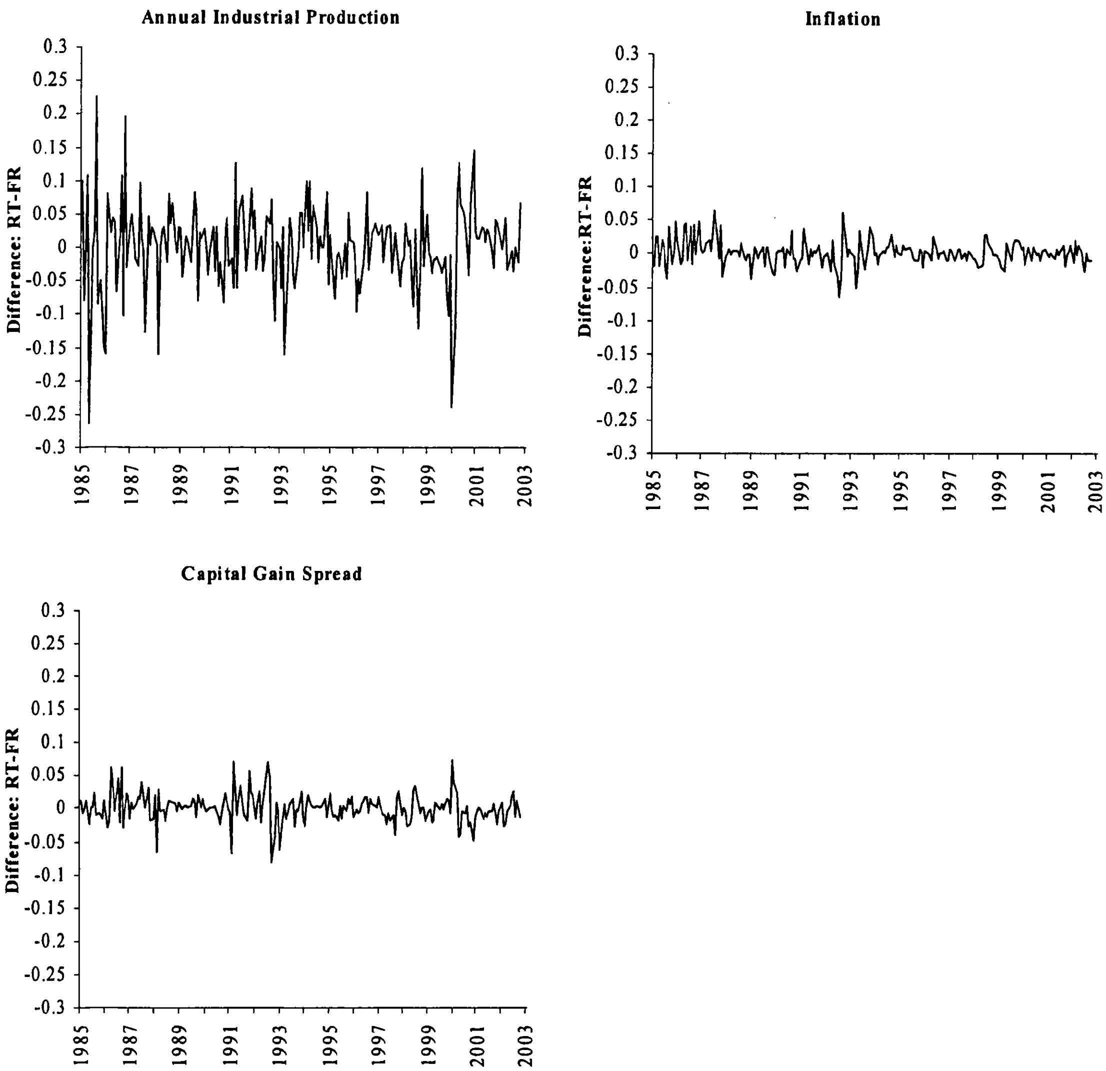
Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling AR(1) models. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes both monthly and annual industrial production growth.

Figure 2.4.7.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling AR(1) Expectations Where Lagged Values are the Most Recent Revision and Including Monthly Industrial Production Growth Innovations Only.



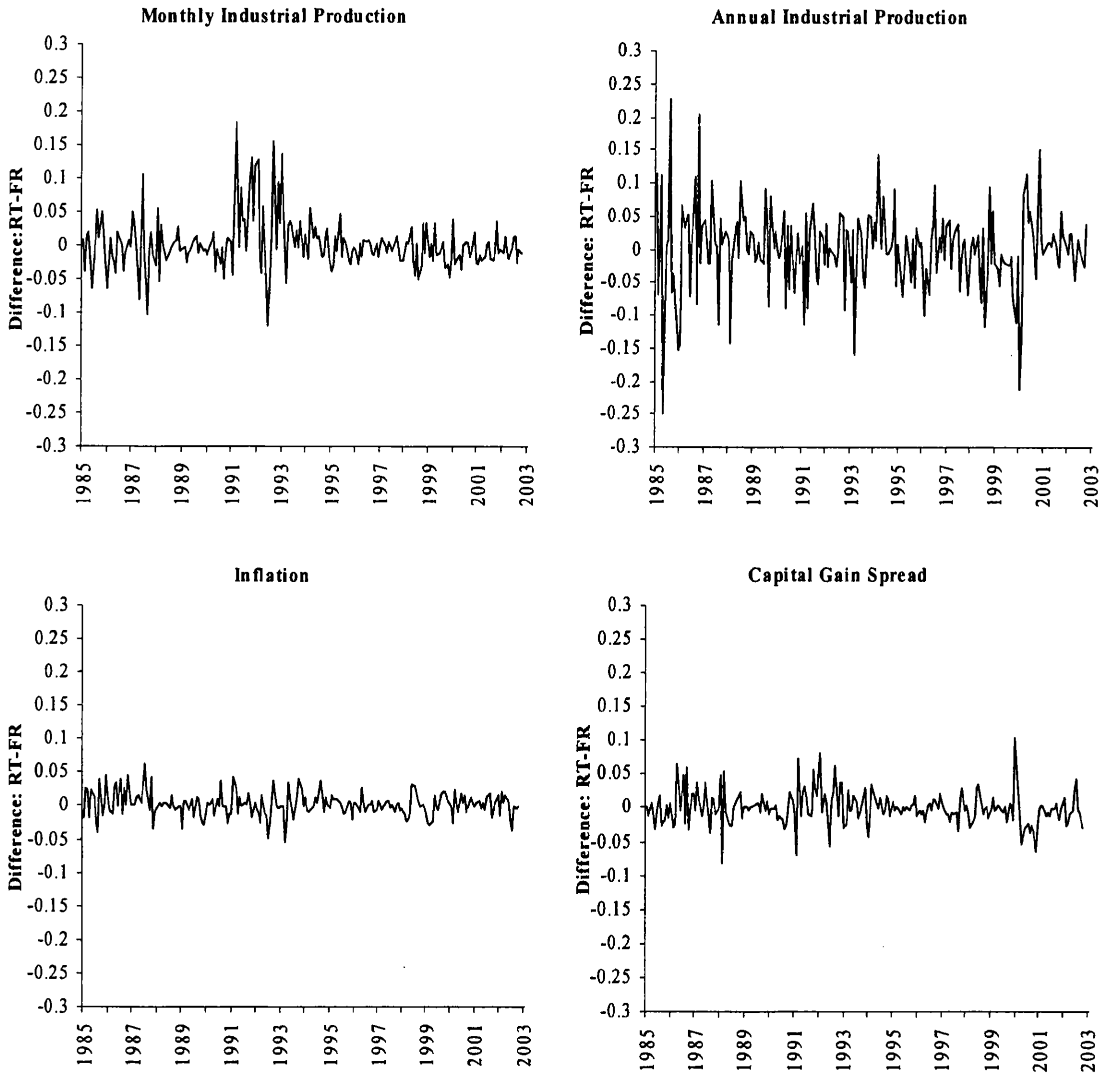
Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling AR(1) models with fully-revised lagged values. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes only monthly industrial production growth.

Figure 2.4.8.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling AR(1) Expectations Where Lagged Values are the Most Recent Revision and Including Annual Industrial Production Growth Innovations Only.



Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling AR(1) models with fully-revised lagged values. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes only annual industrial production growth.

Figure 2.4.9.
Time Series Plots of Market Price of Risk Differentials Assuming Rolling AR(1) Expectations Where Lagged Values are the Most Recent Revision and Including Both Monthly and Annual Industrial Production Growth Innovations.



Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Expectations are measured using rolling AR(1) models with fully-revised lagged values. The graphs show time series of the difference between the market price of risk using real-time data and fully-revised data. The specification of the returns generating model includes both monthly and annual industrial production growth.

Finally, more sophisticated Vector Autoregressive (VAR) models are used to represent expectations in stage 1 to further appraise the impact of expectations assumptions on the pricing of macroeconomic risk factors. Dummy variables and the term structure are excluded from the specification of stage 2 estimations to allow consistent comparison with the more parsimonious expectations models presented in section 2.3.4. Consistent pricing patterns across these different models and assumptions confirm that the findings presented in section 2.4 are robust.

2.5.1 Dummy Variables

The sample period for this study runs from January 1980 to October 2001 and includes two major stock market crashes in October and November 1987 and September 2001, when investors witnessed large negative returns that were not caused by the macroeconomic risk factors used in this study. Stock market crashes cannot be predicted in real-time and so to maintain a strict ex-ante approach to this study, these extreme months are not treated any differently in the econometric methodology explained in section 2.3.4. To maintain a fair comparison between data vintages, the stock market crashes are included in the fully-revised study as well as the real-time study. An ex-post approach in a retrospective study would employ dummy variables to remove possible spurious effects generated during these months, thereby ensuring that statistics and inferences are not determined by these outliers. The estimation is repeated here with dummy variables included such that the equations at stage 2 of the procedure become:

$$r_{p,s+t} = \beta_{0,p,w}^{FR} + \beta_{d,p,w}^{FR} D + \beta_{y,p,w}^{FR}\left({}_{s+t}y_n - {}_{s+t}\hat{y}_n\right) + \beta_{\pi,p,w}^{FR}\left({}_{s+t}\pi_n - {}_{s+t}\hat{\pi}_n\right) + \beta_{c,p,w}^{FR}\left({}_{s+t-i}c_{s+t}\right) + \xi_{p,s+t}^{FR}, \tag{2.12a}$$

$$r_{p,s+t} = \beta_{0,p,w}^{RT} + \beta_{d,p,w}^{RT} D + \beta_{y,p,w}^{RT}\left({}_{s+t-i}y_{s+t} - {}_{s+t-i}\hat{y}_{s+t}\right) + \beta_{\pi,p,w}^{RT}\left({}_{s+t-i}\pi_{s+t} - {}_{s+t-i}\hat{\pi}_{s+t}\right) + \beta_{c,p,w}^{RT}\left({}_{s+t-i}c_{s+t}\right) + \xi_{p,s+t}^{RT}, \tag{2.12b}$$

$$r_{p,s+t} = \beta_{0,p,w}^{RTL} + \beta_{d,p,w}^{RTL} D + \beta_{y,p,w}^{RTL}\left({}_{s+t-i}y_{s+t} - {}_{s+t-i}\tilde{y}_{s+t}\right) + \beta_{\pi,p,w}^{RTL}\left({}_{s+t-i}\pi_{s+t} - {}_{s+t-i}\tilde{\pi}_{s+t}\right) + \beta_{c,p,w}^{RTL}\left({}_{s+t-i}c_{s+t}\right) + \xi_{p,s+t}^{RTL}, \tag{2.12c}$$

where all variables are defined as in section 2.3.4; $\xi^{FR}_{p,s+t}$, $\xi^{RT}_{p,s+t}$ and $\xi^{RTL}_{p,s+t}$ are error terms and D is a qualitative dummy variable that takes the value 1 for the crash months of October and November 1987 and September 2001 and 0 for all other months of the sample. The associated estimated coefficients, $\hat{\beta}^{FR}_{d,p,w}$, $\hat{\beta}^{RT}_{d,p,w}$ and $\hat{\beta}^{RTL}_{d,p,w}$, measure the effect on portfolio returns of the stock market crashes. Inclusion of these intercept dummy variables ensures that estimates of risk factor sensitivities, $\hat{\beta}^{FR}_{k,p,w}$, $\hat{\beta}^{RT}_{k,p,w}$ and $\hat{\beta}^{RTL}_{k,p,w}$ ($k=y$, π or c), are not biased by these months of extreme negative stock portfolio returns. Equation (2.12a) applies fully-revised macroeconomic data implying that returns for month $s+t$ are determined by information not available to traders until long after this month. Specification (2.12b) estimates factor sensitivities using real-time data, thus matching returns in month $s+t$ to macroeconomic information publicly available in month $s+t$. Finally, (2.12c) differentiates the AR(1) expectations models described in equations (2.8e) and (2.8f) from the orthodox AR(1) identified in equations (2.8c) and (2.8d) for real-time data.

Table 2.5.1.1 reports the average estimated market price of risk for macroeconomic risk factors measured using fully-revised data where the specification of the returns generating model in stage 2 of the econometric methodology includes dummy variables to control for stock market crashes. Table 2.5.1.2 reports the same statistics for the macroeconomic risk factors measured using real-time data.[25] Both tables confirm the previous findings of section 2.4. When measured using fully-revised data, according to Table 2.5.1.1, none of the macroeconomic variables are significantly priced, implying that they do not represent pervasive risk factors that are rewarded in the stock market. However, as shown by Table 2.5.1.2, when macroeconomic innovations are calculated from more meaningful real-time data, unanticipated inflation and economic uncertainty are important priced factors and predictors of stock returns. More importantly, the inference levels of the significant average prices of risk are very similar between the ex-ante approach whose results are shown in Table 2.4.2 and the method that controls for stock market crashes whose results are reported in Table 2.5.1.2.

[25] Although not documented, the dummy variables are always statistically significant at the 5% level at least, motivating this discussion of the robustness of risk pricing relationships between data vintages to the explicit modelling of these extreme months.

Table 2.5.1.1. Average Estimated Market Prices of Risk for Fully-Revised Macroeconomic Factors Controlling for the Influence of Stock Market Crashes.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Constant Expectations					
Average price of risk	**0.0027***	-0.0008		-0.0001	0.0030
Standard error	0.0013	0.0019		0.0007	0.0025
	(2.0293)	(-0.4418)		(-0.1103)	(1.1793)
Average price of risk	**0.0031***		-0.0012	-0.0003	0.0032
Standard error	0.0014		0.0043	0.0008	0.0024
	(2.2866)		(-0.2806)	(-0.4375)	(1.3252)
Average price of risk	**0.0032***	-0.0012	-0.0038	-0.0004	0.0027
Standard error	0.0015	0.0019	0.0046	0.0008	0.0025
	(2.2139)	(-0.6178)	(-0.8172)	(-0.5852)	(1.0853)
(B) AR(1) Expectations					
Average price of risk	**0.0034***	-0.0014		-0.0005	0.0033
Standard error	0.0014	0.0020		0.0007	0.0025
	(2.4326)	(-0.6935)		(-0.7321)	(1.3551)
Average price of risk	**0.0033****		-0.0034	-0.0003	0.0031
Standard error	0.0013		0.0025	0.0007	0.0023
	(2.5813)		(-1.3973)	(-0.4708)	(1.3435)
Average price of risk	**0.0035***	-0.0017	-0.0031	-0.0008	0.0031
Standard error	0.0014	0.0021	0.0027	0.0007	0.0023
	(2.4168)	(0.8054)	(-1.1600)	(-1.1666)	(1.3075)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities. Risk factors are measured using fully-revised macroeconomic variables. Dummy variables included in stage 2 regressions to control for months of stock market crashes. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero.

Table 2.5.1.2. Average Estimated Market Prices of Risk for Real-Time Macroeconomic Factors Controlling for the Effect of Stock Market Crashes.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Constant Expectations					
Average price of risk	**0.0025+**	-0.0012		**0.0020***	**0.0042+**
Standard error	0.0013	0.0018		0.0009	0.0022
	(1.8801)	(-0.6884)		(2.2012)	(1.8818)
Average price of risk	**0.0028***		-0.0028	**0.0015+**	**0.0041+**
Standard error	0.0013		0.0042	0.0009	0.0023
	(2.1572)		(-0.6542)	(1.6632)	(1.7673)
Average price of risk	**0.0029***	-0.0002	-0.0034	0.0014	0.0031
Standard error	0.0013	0.0018	0.0043	0.0009	0.0023
	(2.1723)	(-0.1090)	(-0.7896)	(1.5497)	(1.3321)
(B) AR(1) Expectations					
Average price of risk	**0.0024+**	-0.0015		**0.0017***	**0.0042+**
Standard error	0.0013	0.0017		0.0009	0.0022
	(1.7963)	(-0.8876)		(1.9656)	(1.8764)
Average price of risk	**0.0023+**		-0.0019	0.0014	**0.0047***
Standard error	0.0013		0.0025	0.0009	0.0022
	(1.7397)		(-0.7794)	(1.5558)	(2.2038)
Average price of risk	0.0020	-0.0006	-0.0020	**0.0016+**	**0.0045***
Standard error	0.0014	0.0017	0.0026	0.0009	0.0022
	(1.4843)	(-0.3671)	(-0.7629)	(1.7632)	(2.0529)
(C) AR(1) Expectations with fully-revised lagged variable					
Average price of risk	**0.0025+**	-0.0018		**0.0016+**	**0.0045***
Standard error	0.0013	0.0017		0.0009	0.0023
	(1.8655)	(-1.0694)		(1.7914)	(1.9611)
Average price of risk	**0.0027***		-0.0028	0.0013	0.0041
Standard error	0.0013		0.0041	0.0009	0.0023
	(2.0996)		(-0.7003)	(1.4974)	(1.7933)
Average price of risk	**0.0033***	0.0001	-0.0046	0.0014	0.0032
Standard error	0.0013	0.0018	0.0042	0.0009	0.0023
	(2.5265)	(0.0720)	(-1.0905)	(1.5533)	(1.3918)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities. Risk factors are measured using real-time macroeconomic variables. Dummy variables included in stage 2 regressions to control for months of stock market crashes. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero.

In only two of nine possible permutations of output specification and expectations assumptions do the significance of the average price of unanticipated inflation change, becoming more significant when including dummy variables. Also, the statistical significance of the pricing relationship for the capital gain spread variable changes in only two of nine cases when dummy variables are included. The remarkable finding of this robustness test is that pricing relationships are very consistent between the two specifications used for stage 2 estimations, showing that the results presented in section 2.4 are robust to the data outliers caused by stock market crashes.

Table 2.5.1.3 reports test statistics of the hypotheses tests that examine the discrepancy in risk pricing between real-time and fully-revised data. In confirmation of the results of section 2.4, the average price of unanticipated inflation risk when measured using real-time data is significantly different from the average price of that same risk when measured using fully-revised data according to the Wald test. In seven of the nine possible permutations of output specifications and expectations models, this difference is statistically significant at the 5% level or smaller, the two remaining statistics significant at the 10% level. Furthermore, for this macroeconomic risk factor, real-time average prices are also significantly greater than fully-revised average prices according to the equality-of-means test, and at the 5% level for five of the nine statistics and the 10% level for the other four. There is no statistical evidence provided in table 2.5.1.3 to suggest that the average price of economic uncertainty is different when using real-time rather than fully-revised data. As explained in section 2.4, this may be because the capital gain spread can only be measured in real-time, meaning that real-time and fully-revised vintages are identical. It is important to note, however, that the contribution of this risk factor to stock pricing is striking when other variables in the returns generating model are measured using real-time data.

In brief summary, the inclusion of dummy variables to control for data outliers caused by stock market crashes in stage 2 regressions has no influence on the findings and inferences drawn in section 2.4. The importance of the unanticipated inflation and economic uncertainty risk factors as determinants and predictors of stock portfolio returns when variables are measured using real-time data remains the powerful conclusion that is not spuriously generated by the inclusion of extreme stock market movements.

Table 2.5.1.3. Hypothesis Tests on the Average Price of Risk Controlling for Stock Market Crashes.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Constant Expectations					
Wald Coeff. Restriction	0.0251	0.0564		**5.3311***	0.2988
	(0.8743)	(0.8126)		(0.0219)	(0.5852)
Equality of Mean	-0.1143	-0.1964		**1.8384***	0.3619
	(0.4545)	(0.4222)		(0.0334)	(0.3588)
Wald Coeff. Restriction	0.0476		0.1361	**3.9588***	0.1402
	(0.8275)		(0.7126)	(0.0479)	(0.7084)
Equality of Mean	-0.1667		-0.3673	**1.6213+**	0.2406
	(0.4338)		(0.3568)	(0.0529)	(0.4050)
Wald Coeff. Restriction	0.0683	0.3129	0.0085	**3.9297***	0.0309
	(0.7940)	(0.5765)	(0.9266)	(0.0488)	(0.8605)
Equality of Mean	-0.1849	0.3275	-0.0413	**1.6265+**	0.0836
	(0.4267)	(0.3717)	(0.4835)	(0.0523)	(0.4667)
(B) AR(1) Expectations					
Wald Coeff. Restriction	0.5945	0.0025		**6.4326***	0.1586
	(0.4416)	(0.9603)		(0.0119)	(0.6909)
Equality of Mean	-0.5223	-0.0439		**1.9839***	0.2598
	(0.3009)	(0.4825)		(0.0240)	(0.3976)
Wald Coeff. Restriction	0.5234		0.347	**3.5869+**	0.5778
	(0.4702)		(0.5565)	(0.0596)	(0.4480)
Equality of Mean	-0.5220		0.4309	**1.5096+**	0.5259
	(0.3010)		(0.3334)	(0.0660)	(0.2996)
Wald Coeff. Restriction	1.1948	0.4283	0.186	**7.1157****	0.3946
	(0.2756)	(0.5136)	(0.6667)	(0.0082)	(0.5306)
Equality of Mean	-0.7340	0.3974	0.2968	**2.1055***	0.4396
	(0.2317)	(0.3457)	(0.3834)	(0.0179)	(0.3302)
(C) AR(1) Expectations with fully-revised lagged variable					
Wald Coeff. Restriction	0.4878	0.0544		**5.4912***	0.2851
	(0.4857)	(0.8158)		(0.0201)	(0.5939
Equality of Mean	-0.4726	-0.1625		**1.8582***	(0.3581
	(0.3184)	(0.4355)		(0.0319)	(0.3602)
Wald Coeff. Restriction	0.1929		0.0196	**3.3660+**	0.1957
	(0.6610)		(0.8889)	(0.0680)	(0.6587)
Equality of Mean	-0.3117		0.1289	**1.4648+**	0.3190
	(0.3777)		(0.4488)	(0.0719)	(0.3749)
Wald Coeff. Restriction	0.0134	1.0669	0.1211	**6.0391***	0.0028
	(0.9080)	(0.3028)	(0.7282)	(0.0148)	(0.9580)
Equality of Mean	-0.0606	0.6588	-0.2969	**1.9417***	0.0487
	(0.4759)	(0.2552)	(0.3834)	(0.0264)	(0.4806)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The Wald test of coefficient restrictions tests the null hypothesis that the average price of risk for real-time macroeconomic risk factors is not significantly different from its fully-revised counterpart. F-statistics are reported along with p-values in parentheses associated with the two-sided alternative hypothesis. The equality of mean t-statistic tests the null hypothesis that the average price of risk for real-time factors is not significantly greater than its fully-revised counterpart. The p-values reported in parentheses are associated with the one-sided alternative and assume unequal variances between samples. **, * and + indicate test statistics that are significant at the 1, 5 and 10% levels respectively.

The discrepancy between real-time and fully-revised risk pricing is also clearly evident from the statistical significance of the average prices of risk factors and the explicit hypotheses tests performed on them, enhancing the notion that great care should be taken when measuring macroeconomic innovations for investigation in a financial study.

2.5.2 Term Structure of Interest Rates

The second robustness test examines whether the term structure of interest rates is also a priced macroeconomic risk factor when added to the returns generating process. This variable was omitted from the methodology explained in section 2.3 on the theoretical econometric grounds that it is likely to capture similar portfolio return sensitivity to the capital gain spread measure of economic uncertainty as both measures include a term structure element in their construction. It may also be argued that the term structure variable is related to inflationary shocks in the sense that unanticipated inflation implies a future tightening of monetary policy and thus higher interest rates. In order to maintain a fair comparison with the results presented in section 2.4 and to ensure an ex ante approach to the testing methodology, unpredictable stock market crashes remain in the sample when estimating risk factor sensitivities in stage 2. Inclusion of the term structure variable in the returns generating process alters the equations estimated in stage 2 of the methodology. They now become:

$$\begin{aligned} r_{p,s+t} = \beta^{FR}_{0,p,w} + \beta^{FR}_{y,p,w}\left({}_{s+t}y_n - {}_{s+t}\hat{y}_n\right) + \beta^{FR}_{\pi,p,w}\left({}_{s+t}\pi_n - {}_{s+t}\hat{\pi}_n\right) \\ + \beta^{FR}_{\tau,p,w}\left({}_{s+t-i}\tau_{s+t}\right) + \beta^{FR}_{c,p,w}\left({}_{s+t-i}c_{s+t}\right) + \zeta^{FR}_{p,s+t}, \end{aligned} \tag{2.13a}$$

$$\begin{aligned} r_{p,s+t} = \beta^{RT}_{0,p,w} + \beta^{RT}_{y,p,w}\left({}_{s+t-i}y_{s+t} - {}_{s+t-i}\hat{y}_{s+t}\right) + \beta^{RT}_{\pi,p,w}\left({}_{s+t-i}\pi_{s+t} - {}_{s+t-i}\hat{\pi}_{s+t}\right) \\ + \beta^{RT}_{\tau,p,w}\left({}_{s+t-i}\tau_{s+t}\right) + \beta^{RT}_{c,p,w}\left({}_{s+t-i}c_{s+t}\right) + \zeta^{RT}_{p,s+t}, \end{aligned} \tag{2.13b}$$

$$\begin{aligned} r_{p,s+t} = \beta^{RTL}_{0,p,w} + \beta^{RTL}_{y,p,w}\left({}_{s+t-i}y_{s+t} - {}_{s+t-i}\tilde{y}_{s+t}\right) + \beta^{RTL}_{\pi,p,w}\left({}_{s+t-i}\pi_{s+t} - {}_{s+t-i}\tilde{\pi}_{s+t}\right) \\ + \beta^{RTL}_{\tau,p,w}\left({}_{s+t-i}\tau_{s+t}\right) + \beta^{RTL}_{c,p,w}\left({}_{s+t-i}c_{s+t}\right) + \zeta^{RTL}_{p,s+t}, \end{aligned} \tag{2.13c}$$

where τ denotes the term structure variable; $\beta^{FR}_{\tau,p,w}$, $\beta^{RT}_{\tau,p,w}$ and $\beta^{RTL}_{\tau,p,w}$ measure the sensitivity of portfolio returns to the term structure during a particular estimation window; $\zeta^{FR}_{p,s+t}$, $\zeta^{RT}_{p,s+t}$ and $\zeta^{RTL}_{p,s+t}$ are error terms and all other variables are as defined in section 2.4.3. Both the term structure of interest rates and the capital gain spread are financial variables, which means they do not require expectations modelling and can only be measured in real-time. Equation (2.13a) applies fully-revised macroeconomic data implying that returns for month $s+t$ are determined by information not available to traders until long after this month. Specification (2.13b) estimates factor sensitivities using real-time data, thus matching returns in month $s+t$ to macroeconomic information publicly available in month $s+t$. Finally, (2.13c) differentiates the AR(1) expectations models described in equations (2.8e) and (2.8f) from the orthodox AR(1) identified in equations (2.8c) and (2.8d) for real-time data.

Tables 2.5.2.1 and 2.5.2.2 report the average prices of macroeconomic risk factors when measured using fully-revised and real-time data respectively. The term structure of interest rates is never priced, regardless of data type, expectations assumptions or real output specification. It is not an important factor for predicting expected equity returns. The inclusion of the term structure has also eliminated the pricing effect of unexpected inflation and has drastically reduced the influence of economic uncertainty. The evidence presented for UK data supports Chen at al. (1986) that the term structure is not important for equity pricing and also justifies the outright exclusion of the term structure by Christoffersen et al. (2002), which is the approach adopted in section 2.3.

Although inclusion of the term structure variable dramatically reduces the statistical significance of average prices of risk, Table 2.5.2.3 shows that there remains a risk pricing discrepancy between data vintages, albeit only a very slight difference. The average price of unanticipated inflation risk measured using real-time data is statistically significantly different from (according to the Wald test) and greater than (according to the equality-of-means test) the average price of unanticipated inflation risk measured using fully-revised data. However, this discrepancy holds at the 10% level of significance and for AR(1) expectations models only.

In summary, whilst an important economic and statistical difference between the average price of unanticipated inflation risk is still evident, the pricing of real-time risk factors and the distinction between risk pricing between data vintages is severely weakened by the inclusion of the term structure of interest rates variable.

Table 2.5.2.1. Average Estimated Market Prices of Risk for Fully-Revised Macroeconomic Factors Including the Term Structure of Interest Rates.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Term Structure	Capital Gain Spread
(A) Constant Expectations						
Average price of risk	0.0021	-0.0008		0.0001	-0.0029	0.0019
Standard error	0.0015	0.0019		0.0007	0.0023	0.0027
	(0.1634)	(-0.4162)		(0.0740)	(-1.2559)	(0.7090)
Average price of risk	**0.0025+**		-0.0010	0.0001	-0.0019	0.0022
Standard error	0.0014		0.0045	0.0007	0.0023	0.0024
	(1.7383)		(-0.2217)	(0.9518)	(-0.8296)	(0.9307)
Average price of risk	0.0023	-0.0012	-0.0028	0.0001	-0.0037	0.0017
Standard error	0.0015	0.0019	0.0047	0.0008	0.0024	0.0026
	(1.5847)	(-0.6250)	(-0.5851)	(0.0851)	(-1.5286)	(0.6743)
(B) AR(1) Expectations						
Average price of risk	**0.0025+**	-0.0013		-0.0003	-0.0031	0.0022
Standard error	0.0016	0.0020		0.0007	0.0023	0.0025
	(1.7200)	(-0.6667)		(-0.4738)	(-1.3894)	(0.8687)
Average price of risk	**0.0025+**		-0.0033	-0.0005	-0.0031	0.0013
Standard error	0.0014		0.0025	0.0007	0.0023	0.0024
	(1.7993)		(-1.3198)	(-0.6658)	(-1.3693)	(0.5611)
Average price of risk	**0.0026+**	-0.0016	-0.0034	-0.0006	-0.0036	0.0018
Standard error	0.0015	0.0020	0.0027	0.0007	0.0023	0.0024
	(1.7735)	(-0.7616)	(-1.2612)	(-0.8213)	(-1.5784)	(0.7594)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities. Risk factors are measured using fully-revised macroeconomic variables. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero.

Table 2.5.2.2. Average Estimated Market Prices of Risk for Real-Time Macroeconomic Factors Including the Term Structure of Interest Rates.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Term Structure	Capital Gain Spread
(A) Constant Expectations						
Average price of risk	0.0016	-0.0006		0.0013	-0.0011	0.0035
Standard error	0.0015	0.0019		0.0009	0.0026	0.0024
	(1.1020)	(-0.3296)		(1.5074)	(-0.4251)	(1.4828)
Average price of risk	0.0018		-0.0009	0.0009	-0.0012	**0.0042+**
Standard error	0.0014		0.0043	0.0009	0.0021	0.0024
	(1.2739)		(-0.2096)	(1.0055)	(-0.5603)	(1.7641)
Average price of risk	0.0016	0.0001	-0.0016	0.0008	-0.0009	0.0035
Standard error	0.0015	0.0018	0.0044	0.0009	0.0022	0.0024
	(1.7093)	(0.0451)	(-0.3646)	(0.9466)	(-0.3948)	(1.4725)
(B) AR(1) Expectations						
Average price of risk	0.0016	-0.0004		0.0012	-0.0006	0.0034
Standard error	0.0015	0.0018		0.0009	0.0026	0.0024
	(1.1205)	(-0.2265)		(1.3952)	(-0.2327)	(1.4586)
Average price of risk	0.0016		-0.0012	0.0008	-0.0007	**0.0042+**
Standard error	0.0015		0.0026	0.0009	0.0024	0.0023
	(1.0866)		(-0.4669)	(0.9524)	(-0.2663)	(1.8717)
Average price of risk	0.0016	0.0011	-0.0019	0.0012	-0.0010	0.0036
Standard error	0.0015	0.0018	0.0026	0.0009	0.0025	0.0023
	(1.0662)	(0.6045)	(-0.7214)	(1.3102)	(-0.3823)	(1.5658)
(C) AR(1) Expectations with fully-revised lagged variable						
Average price of risk	0.0018	-0.0004		0.0012	-0.0009	0.0037
Standard error	0.0015	0.0017		0.0009	0.0022	0.0024
	(1.2388)	(-0.2181)		(1.3401)	(0.6685)	(1.5457)
Average price of risk	0.0018		-0.0007	0.0007	-0.0008	**0.0041+**
Standard error	0.0014		0.0042	0.0008	0.0021	0.0024
	(1.2419)		(-0.1662)	(0.8387)	(-0.3801)	(1.7438)
Average price of risk	0.0018	0.0003	-0.0022	0.0009	-0.0007	0.0036
Standard error	0.0014	0.0018	0.0042	0.0008	0.0022	0.0024
	(1.2772)	(0.1837)	(-0.5190)	(1.0934)	(-0.3208)	(1.5185)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities. Risk factors are measured using real-time macroeconomic variables. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated t-statistics shown in parentheses. **, *, + indicate t-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant t-statistics imply that the average price of risk is significantly different from zero.

Table 2.5.2.3. Hypothesis Tests on the Average Price of Risk Including the Term Structure of Interest Rates.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Term Structure	Capital Gain Spread
(A) Constant Expectations						
Wald Coeff. Restriction	0.1048	0.0108		1.9445	0.4980	0.4599
	(0.7465)	(0.9174)		(0.1646)	(0.4812)	(0.4984)
Equality of Mean	-0.2041	0.0740		1.1217	0.5230	0.4553
	(0.4192)	(0.4705)		(0.1313)	(0.3006)	(0.3246)
Wald Coeff. Restriction	0.2156		0.0006	0.7934	0.1132	0.6944
	(0.6429		(0.9813)	(0.3741)	(0.7369)	(0.4056)
Equality of Mean	-0.3264		0.0145	0.7260	0.2355	0.5786
	(0.3721)		(0.4942)	(0.2341)	(0.4070)	(0.2816)
Wald Coeff. Restriction	0.2516	0.5290	0.0756	0.6948	1.6290	0.5735
	(0.6165)	(0.4678)	(0.7836)	(0.4055)	(0.2032)	(0.4497)
Equality of Mean	-0.3674	0.4896	0.1800	0.6673	0.8606	0.5063
	(0.3567)	(0.3123)	(0.4286)	(0.2525)	(0.1950)	(0.3065)
(B) AR(1) Expectations						
Wald Coeff. Restriction	0.3475	0.2406		**3.0628+**	0.8838	0.2715
	(0.5561)	(0.6243)		(0.0815)	(0.3482)	(0.6029)
Equality of Mean	-0.4212	0.3335		**1.3742+**	0.7231	0.7231
	(0.3369)	(0.3694)		(0.0851)	(0.2350)	(0.2350)
Wald Coeff. Restriction	0.3453		0.6815	2.3634	1.0046	1.6854
	(0.5574)		(0.4100)	(0.1257)	(0.3173)	(0.1956)
Equality of Mean	-0.4399		0.5835	1.1567	0.7375	0.8898
	(0.3301)		(0.2799)	(0.1240)	(0.2306)	(0.1870)
Wald Coeff. Restriction	0.4558	2.2401	0.3487	**3.9661***	1.0695	0.6106
	(0.5003)	(0.1359)	(0.5555)	(0.0477)	(0.3022)	(0.4354)
Equality of Mean	-0.4979	0.9710	0.4141	**1.5322+**	0.7741	0.5279
	(0.3094)	(0.1661)	(0.3395)	(0.0631)	(0.2196)	(0.2989)
(C) AR(1) Expectations with fully-revised lagged variable						
Wald Coeff. Restriction	0.2315	0.3000		**2.8467+**	0.9629	0.3943
	(0.6309)	(0.5844)		(0.0930)	(0.3276)	(0.5307)
Equality of Mean	-0.3435	0.3593		**1.3373+**	0.6937	0.4302
	(0.3657)	(0.3598)		(0.0909)	(0.2441)	(0.3336)
Wald Coeff. Restriction	0.2618		0.3941	2.0629	1.2149	1.4243
	(0.6094)		(0.5308)	(0.1524)	(0.2716)	(0.2340)
Equality of Mean	-0.3766		0.5326	1.0697	0.7502	0.8350
	(0.3533)		(0.2973)	(0.1427)	(0.2268)	(0.2021)
Wald Coeff. Restriction	0.2888	1.1859	0.0820	**3.2703+**	1.6555	0.5684
	(0.5915)	(0.2774)	(0.7749)	(0.0720)	(0.1996)	(0.4517)
Equality of Mean	-0.3929	0.6954	0.2456	**1.3637+**	0.9057	0.5160
	(0.3473)	(0.2436)	(0.4031)	(0.0867)	(0.1828)	(0.3031)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The Wald test of coefficient restrictions tests the null hypothesis that the average price of risk for real-time macroeconomic risk factors is not significantly different from its fully-revised counterpart. F-statistics are reported along with p-values in parentheses associated with the two-sided alternative hypothesis. The equality of mean t-statistic tests the null hypothesis that the average price of risk for real-time factors is not significantly greater than its fully-revised counterpart. The p-values reported in parentheses are associated with the one-sided alternative and assume unequal variances between samples. **, * and + indicate test statistics that are significant at the 1, 5 and 10% levels respectively.

As with the capital gain spread measure discussed in section 2.4, the term structure is also a financial variable that is measured identically in real-time and under full revision. The lack of evidence of a discrepancy between real-time and fully-revised average prices of risk for the term structure and capital gain spread may not be surprising given that both variables can only be observed in real-time. The economic and statistical contributions of the unanticipated inflation, capital gains spread and term structure variables towards the pricing of stocks and the prediction of their returns are diminished by the inclusion of the term structure in the returns generating model.

Although not reported, repetition of the procedure using a returns generating model that includes real output, inflation and term structure innovations also reveals no priced macroeconomic risk factors. This shows that economic uncertainty, measured by the capital gain spread, is an important factor generating stock returns, and that there is no collinearity between it and the term structure. This effect of the term structure on risk pricing cannot be attributed to the inclusion of an irrelevant variable either, since estimates of the market price of risk remains unbiased under this type of mis-specification.[26] Despite a lack of statistical evidence, pricing discrepancies between models (2.9) and (2.13) may be explained intuitively. As previously noted, the capital gain spread variable is not completely void of term structure effects because of the constraint on the availability of UK data in its construction. Unanticipated inflation may also be interpreted as a signal of tighter future monetary policy, which could measure the same effects as an explicit term structure variable. An overlap between variables is not evident as statistical correlation between factor sensitivities, but it can be argued that sensitivity of returns to inflation shocks and economic uncertainty may also be including some term structure effects, justifying the exclusion of the term structure variable in equations (2.9).

2.5.3 Vector Autoregressive (VAR) Expectations

The third robustness test employs a more sophisticated structure to the modelling of expectations to evaluate whether risk pricing relationships identified in section 2.4

[26] Explicit correlation tests show no evidence that equations (2.13) include an irrelevant variable, no evidence of correlation between variables in equations (2.9) or (2.13) and no evidence of the omission of a relevant variable in equations (2.9).

are influenced by assumptions concerning economic expectations. First order autoregressive processes as defined by equations (2.8a) to (2.8f) regress the current value of a particular variable on that variable's value in the previous period. The VAR approach advances on the simple AR(1) expression by modelling every endogenous variable in the system as a function of all the endogenous variables in the system. A first order VAR model is chosen to conserve the number of observations to be used in each fixed 60 month estimation window of stage 1 and is specified as follows:

$$ {}_{s+t}\kappa_n = \phi^{FR} 1 + \delta^{FR} \; {}_{s+t-1}\kappa_n + \omega^{FR}_{s+t}, \tag{2.14a}$$

$$ {}_{s+t-i}\kappa_{s+t} = \phi^{RT} 1 + \delta^{RT} \; {}_{s+t-i-1}\kappa_{s+t-1} + \omega^{RT}_{s+t}, \tag{2.14b}$$

where ${}_{s+t}\kappa_n$ and ${}_{s+t-i}\kappa_{s+t}$ are (3x1) vectors of fully-revised and real-time macroeconomic variables y, π and c (the endogenous variables) respectively; 1 is a (3x1) vector of 1's such that ϕ^{FR} and ϕ^{RT} are (3x3) diagonal matrices of constants (the exogenous variables) to be estimated; ${}_{s+t-1}\kappa_n$ and ${}_{s+t-i-1}\kappa_{s+t-1}$ are (3x1) vectors of the fully-revised and real-time macroeconomic variables lagged by one period such that δ^{FR} and δ^{RT} are (3x3) matrices of coefficients to be estimated and ω^{FR}_{s+t} and ω^{FR}_{s+t} are (3x1) vectors of error terms.[27] All other variables are as defined in section 2.3.4 and the VAR models are estimated using the familiar 60 month rolling window procedure. Equation (2.14a) shows the VAR expectations system applied to conventional fully-revised macroeconomic data, whereas equations (2.14b) uses more realistic real-time formulations that assume traders anticipate preliminary releases of output and inflation because these form the basis of their real-time information set and hence asset valuations. These are based explicitly on information available to traders at time $s+t$ and are therefore contemporaneous with returns for month $s+t$. The residuals from the estimations of equations (2.14a) and (2.14b) measure macroeconomic innovations. Stages 2 to 4 of the econometric methodology then proceed as normal, such that the only difference between this robustness test

[27] Note that the capital gain spread risk factor is identical between data vintages.

and the methodology presented in section 2.3 is an alternative calculation of macroeconomic innovations.

Table 2.5.3.1 displays the empirical results obtained for the estimated market prices of the risk factors using a first order VAR model to measure expectations. Panel (A) shows the results when macroeconomic innovations are measured using fully-revised data, whilst Panel (B) shows the corresponding results when using real-time macroeconomic data. The results are consistent with the models of expectations described in section 2.3, whose results are discussed in section 2.4, showing that both the risk pricing relationships and discrepancies between real-time and fully-revised data vintages are robust to different assumptions regarding economic expectations. Using fully-revised data, economic variables play no role in the prediction of stock returns since none of the average prices of risk in Panel (A) are significantly different from zero.

When risk factors are calculated using real-time data, as shown in Panel (B), the average price of inflation surprises is significantly different from zero at the 5% significance level when the monthly real output innovations is included in the returns generating model, and at the 10% significance level when both monthly and annual real output innovations are included. Economic uncertainty, as measured by the capital gain spread, is also a significantly priced risk factor, shown by the average price of risk being statistically different from zero at the 5% significance level in two of the three real output specifications and at the 10% significance level for the other. These results confirm the importance of inflation surprises and economic uncertainty as pervasive risk factors influencing stock returns. Thus stocks whose returns are positively correlated with inflation shocks and uncertainty offer a higher expected rate of return and are therefore more valuable.

Finally, Table 2.5.3.2 reports the results of hypotheses tests performed on the average prices of risk factors that investigate the discrepancy in risk pricing evident between real-time and fully-revised macroeconomic factors. In support of the results reported in section 2.4, the Wald test of coefficient restrictions shows that the average price of inflation risk, when inflation shocks are measured using real-time data, is statistically different from the average price of inflation risk measured using fully-revised data at the 5% level of significance.

Table 2.5.3.1. Average Estimated Market Prices of Macroeconomic Factors Using VAR Expectations.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Fully-revised Data					
Average price of risk	0.0021	-0.0018		-0.0005	0.0035
Standard error	0.0015	0.0022		0.0007	0.0025
	(1.4254)	(-0.8534)		(-0.6322)	(1.3963)
Average price of risk	0.0019		-0.0031	-0.0001	0.0027
Standard error	0.0014		0.0026	0.0007	0.0023
	(1.3048)		(-1.1902)	(-0.2025)	(1.1829)
Average price of risk	0.0025	-0.0021	-0.0033	-0.0006	0.0024
Standard error	0.0015	0.0021	0.0029	0.0007	0.0023
	(1.5979)	(-0.9689)	(-1.1218)	(-0.8410)	(1.0611)
(B) Real-Time Data					
Average price of risk	0.0014	-0.0016		**0.0018***	**0.0038+**
Standard error	0.0015	0.0017		0.0009	0.0022
	(0.9840)	(-0.9846)		(1.9851)	(1.7141)
Average price of risk	0.0015		-0.0017	0.0013	**0.0050***
Standard error	0.0015		0.0023	0.0009	0.0021
	(1.0087)		(-0.7136)	(1.4864)	(2.4227)
Average price of risk	0.0017	-0.0007	-0.0017	**0.0017+**	**0.0047***
Standard error	0.0015	0.0016	0.0022	0.0009	0.0021
	(1.1574)	(-0.4341)	(-0.7539)	(1.8525)	(2.2172)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities. Macroeconomic innovations are calculated from VAR expectations models. In Panel (A) risk factors are measured using fully-revised macroeconomic variables, whilst in Panel (B) risk factors are measured using real-time macroeconomic variables. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero.

Table 2.5.3.2. Hypothesis Tests on Average Prices of Risk Using VAR Expectations.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
Wald Coeff. Restriction	0.2000	0.0094		**6.4741***	0.0149
	(0.6552)	(0.9228)		(0.0117)	(0.9029)
Equality of Mean	-0.3137	0.0716		**1.9469***	0.0868
	(0.3769)	(0.4715)		(0.0261)	(0.4654)
Wald Coeff. Restriction	0.0841		0.3940	2.5567	1.2516
	(0.7721)		(0.5309)	(0.1113)	(0.2645)
Equality of Mean	-0.1933		0.4090	**1.3096+**	0.7400
	(0.4234)		(0.3414)	(0.0956)	(0.2298)
Wald Coeff. Restriction	0.2903	0.8057	0.5467	**6.3464***	1.1592
	(0.5906)	(0.3704)	(0.4605)	(0.0125)	(0.2829)
Equality of Mean	-0.3542	0.5185	0.4409	**1.9840***	0.7400
	(0.3617)	(0.3022)	(0.3298)	(0.0240)	(0.2299)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The Wald test of coefficient restrictions tests the null hypothesis that the average price of risk for real-time macroeconomic risk factors is not significantly different from its fully-revised counterpart. *F*-statistics are reported along with *p*-values in parentheses associated with the two-sided alternative hypothesis. The equality of mean *t*-statistic tests the null hypothesis that the average price of risk for real-time factors is not significantly greater than its fully-revised counterpart. The *p*-values reported in parentheses are associated with the one-sided alternative and assume unequal variances between samples. **, * and + indicate test statistics that are significant at the 1, 5 and 10% levels respectively.

The equality-of-means test also reported in Table 2.5.3.2 provides statistical evidence that the average price of inflation risk is greater for real-time data than fully-revised data, also at the 5% level of significance. There is no evidence of a discrepancy in risk pricing between data vintages for the capital gain spread variable according to Table 2.5.3.2, which offers strong support to the other findings reported so far. The capital gain spread is a financial variable so it is measured identically in real-time and full revision and this may explain the lack of direct evidence of any discrepancy in risk pricing. Arguably, of greater importance are this variable's economic and statistical contributions to risk pricing, which are only evident when all variables in the returns generating model are recorded using real-time data, emphasising the importance of data measurement for financial studies incorporating macroeconomic variables.

This final robustness test confirms that the discovery of unanticipated inflation and economic uncertainty as crucial pervasive macroeconomic risk factors influencing expected stock returns and the discrepancy in risk pricing caused by the inaccurate measurement of the true information set held by stock market participants by using fully-revised rather than real-time macroeconomic data are not specific to the models used to proxy the underlying formation of economic expectations.

2.6 ASYMMETRY OVER THE BUSINESS CYCLE

An innovative extension to the work of Christoffersen et al. (2002) enhances previous research of McQueen and Roley (1993) to investigate the possibility that stock pricing may be influenced by different factors at different stages of the business cycle. The time series of estimates of the market prices of risk obtained from equations (2.10a)-(2.10c) are ordered by industrial production growth rate. They are then sorted into two sub-samples designed to represent periods of economic expansion and contraction, with estimations (2.11a)-(2.11c) performed on each sub-sample. The expansion sub-sample includes estimates in months where industrial production is not contracting, meaning that the growth rate is greater than or equal to zero.[28] The contraction sub-sample includes estimates for months during which industrial production was contracting and its growth rate was negative. Real-time

[28] Although a zero growth rate does not signal economic expansion, there are only a very small number of months for which this is the case and so grouping zero growth months in with positive growth months is not expected to bias the results.

estimates are sorted by the growth rate of real-time industrial production data releases, whereas fully-revised data are sorted by the growth rate of fully-revised industrial production data.

The average market prices of risk factors, their associated White (1980) heteroscedasticity consistent standard errors and t-statistics are shown in Tables 2.6.1 for macroeconomic factors measured using fully-revised data and 2.6.2 for factors measured using real-time data. Panel (A) of each table shows the risk pricing relationships during times of expansion, whilst those for periods of economic contraction are displayed in Panel (B). Tables 2.6.1 and 2.6.2 report only the results assuming first order autoregressive expectations.[29] Critical values of the t-distribution are adjusted to allow for different sample sizes between the expansion and contraction periods.

The common theme of the results of section 2.4 is again evident in Tables 2.6.1 and 2.6.2. That is, different results, inferences and interpretations are obtained when using different data vintages to measure macroeconomic factors. Consistent with the results of section 2.4 and the robustness tests of section 2.5, fully-revised data leads researchers to conclude that there is no empirical evidence to support APT and economic variables are not important factors for the valuation of stocks. This is shown in Table 2.6.1 where none of the average market prices of risk are significantly different from zero for any of the risk factors. Real-time data, however, offers support for APT and suggests that inflation shocks and economic uncertainty are risk factors that are rewarded in the stock market. The average price of risk, according to Table 2.6.2, is statistically significant at the 1% level in two of the three output specifications for unanticipated inflation, and at the 5% level in the same output specifications for the capital gain spread.

More importantly, this extension of the study reveals that the pricing influences of unexpected inflation and uncertainty are not symmetric over the business cycle. Each priced risk factor is only influential in driving stock returns during periods when those risks are most prevalent. Thus, industrial production expands as firms build up inventories to satisfy increasing demand for their products. Stronger aggregate demand is likely to induce inflationary pressures throughout the economy and inflation tends to be more volatile at higher levels.

[29] In order to maintain consistency with the results displayed in section 2.4, stock market crashes are included in the sample since they cannot be predicted in real-time.

Table 2.6.1. Risk Pricing Over the Business Cycle Using Fully-Revised Macroeconomic Factors.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Expansion					
Average price of risk	**0.0034+**	-0.0013		-0.0005	0.0027
Standard error	0.0018	0.0027		0.0009	0.0033
	(1.9183)	(-0.4703)		(-0.5572)	(0.8128)
Average price of risk	**0.0039***		-0.0054	-0.0006	0.0015
Standard error	0.0017		0.0035	0.0009	0.0032
	(2.1294)		(-1.5253)	(-0.6643)	(0.4721)
Average price of risk	0.0036	-0.0016	-0.0058	-0.0012	0.0025
Standard error	0.0019	0.0029	0.0038	0.0009	0.0031
	(1.9132)	(-0.5675)	(-1.5352)	(-1.3835)	(0.8020)
(B) Contraction					
Average price of risk	-0.0001	-0.0027		-0.0002	0.0043
Standard error	0.0025	0.0028		0.0012	0.0039
	(-0.0392)	(-0.9728)		(-0.1269)	(1.1160)
Average price of risk	-0.0007		-0.0011	0.0002	0.0056
Standard error	0.0024		0.0035	0.0011	0.0035
	(-0.3129)		(-0.3021)	(0.1368)	(1.6106)
Average price of risk	0.0000	-0.0027	-0.0004	0.0003	0.0039
Standard error	0.0025	0.0029	0.0038	0.0012	0.0037
	(-0.0166)	(-0.9309)	(-0.1162)	(0.2366)	(1.0543)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Risk factors are measured using fully-revised macroeconomic variables. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant, allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero. Panel (A) includes estimates of market prices of risk during months when industrial production was not contracting and Panel (B) includes estimates during months when industrial production was contracting.

Table 2.6.2. Risk Pricing Over the Business Cycle Using Real-Time Macroeconomic Factors.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) Expansion					
Average price of risk	0.0032	-0.0028		**0.0037****	0.0022
Standard error	0.0022	0.0023		0.0013	0.0032
	(1.4762)	(-1.2203)		(2.9594)	(0.6996)
Average price of risk	0.0030		-0.0027	**0.0033***	0.0040
Standard error	0.0022		0.0035	0.0013	0.0031
	(1.3442)		(-0.7558)	(2.5807)	(1.2804)
Average price of risk	0.0030	-0.0005	-0.0037	**0.0037****	0.0027
Standard error	0.0023	0.0023	0.0037	0.0013	0.0031
	(1.3384)	(-0.2265)	(0.9814)	(2.8054)	(0.8756)
(B) Contraction					
Average price of risk	-0.0008	-0.0002		-0.0006	**0.0064***
Standard error	0.0019	0.0024		0.0012	0.0032
	(-0.4073)	(-0.1019)		(-0.4701)	(1.9972)
Average price of risk	-0.0006		-0.0016	-0.0009	**0.0057+**
Standard error	0.0019		0.0034	0.0012	0.0030
	(-0.2856)		(-0.4696)	(-0.7403)	(1.8704)
Average price of risk	-0.0010	-0.0010	-0.0008	-0.0009	**0.0064***
Standard error	0.0019	0.0023	0.0035	0.0011	0.0031
	(-0.4998)	(-0.4197)	(-0.2177)	(-0.7677)	(2.0723)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. Risk factors are measured using real-time macroeconomic variables. Time series mean prices of risk are calculated by regressing estimated prices of risk on a constant, allowing standard errors to be computed using White (1980) heteroscedasticity consistent covariances, with associated *t*-statistics shown in parentheses. **, *, + indicate *t*-statistics that are statistically significant at the 1, 5 and 10% level of significance. Statistically significant *t*-statistics imply that the average price of risk is significantly different from zero. Panel (A) includes estimates of market prices of risk during months when industrial production was not contracting and Panel (B) includes estimates during months when industrial production was contracting.

The data in Table 2.6.2 indicates that during such expansionary periods unanticipated inflation is the most important factor determining expected stock returns. Weaker aggregate demand signals an economic downturn and prompts firms to reduce production. Declining orders, sales, revenue and profit all increase the risk of bankruptcy and uncertainty surrounding the ability of firms to maintain cash flows and returns to their investors, creating a more uncertain investment climate. During months when industrial production was contracting, Table 2.6.2 shows evidence that economic uncertainty is the most important factor driving equity returns.

Table 2.6.3 presents further investigative analysis to determine whether the average prices of risk are statistically different between data vintages. According to the test statistics, there is strong evidence at the 1% level that the average price of real-time unanticipated inflation is significantly different from and statistically greater than the average price of inflationary shocks measured with fully-revised data. Crucially, this is only the case during expansionary phases of the business cycle, as evidenced by significant test statistics in Panel (A) and insignificant test statistics in Panel (B), showing that the discrepancy between the pricing of this risk factor between data vintages is also highly asymmetric appearing only during phases of the business cycle when that risk is most prevalent. Panel (C) of Table 2.6.3 confirms this business cycle asymmetry, showing that, when using only real-time data, the average price of unanticipated inflation during expansions is significantly different from and greater than the same risk during periods of contraction.

As with the full sample results of section 2.4, there is no significant statistical difference between average prices of risk for economic uncertainty between data vintages, which may be explained by the fact that the capital gain spread measure can only be measured in real-time. The economic and statistical contributions of this variable as a predictor of stock returns, however, only become apparent when the other variables of the returns generating process are measured using real-time data, and specifically during periods of the business cycle when that risk is at its greatest.

2.7 CONCLUSION

The results and interpretations from this test of the APT are markedly different when using real-time and fully-revised macroeconomic data.

Table 2.6.3. Hypothesis Tests for Average Prices of Risk Across the Business Cycle.

	Constant	Monthly Industrial Production	Annual Industrial Production	Inflation	Capital Gain Spread
(A) RT Expansion vs FR Expansion					
Wald Coeff. Restriction	0.0060	0.4336		**11.2832****	0.0220
	(0.9386)	(0.5116)		(0.0011)	(0.8825)
Equality of Mean	-0.0734	-0.4334		**2.7496****	-0.0998
	(0.4708)	(0.3326)		(0.0033)	(0.4603)
Wald Coeff. Restriction	0.1567		0.6038	**9.2858****	0.6404
	(0.6930)		(0.4388)	(0.0029)	(0.4255)
Equality of Mean	-0.2979		0.5484	**2.4948****	0.5675
	(0.3831)		(0.2920)	(0.0067)	(0.2855)
Wald Coeff. Restriction	0.0650	0.2141	0.3227	**13.895****	0.0058
	(0.7992)	(0.6445)	(0.5771)	(0.0003)	(0.9395)
Equality of Mean	-0.1846	0.2968	0.4012	**3.0984****	0.0546
	(0.4269)	(0.3835)	(0.3443)	(0.0011)	(0.4783)
(B) RT Contraction vs FR Contraction					
Wald Coeff. Restriction	0.1254	1.0820		0.0901	0.4250
	(0.7240)	(0.3008)		(0.7647)	(0.5160)
Equality of Mean	-0.2152	0.6799		-0.2417	0.4178
	(0.4149)	(0.2487)		(0.4047)	(0.3383)
Wald Coeff. Restriction	0.0062		0.0213	0.8304	0.0006
	(0.9372)		(0.8843)	(0.3643)	(0.9810)
Equality of Mean	0.0626		-0.1102	-0.6267	0.0069
	(0.4751)		(0.4562)	(0.2658)	(0.4973)
Wald Coeff. Restriction	0.2498	0.5359	0.0110	1.0660	0.6546
	(0.6183)	(0.4658)	(0.9186)	(0.3043)	(0.4204)
Equality of Mean	-0.2901	0.4630	-0.0600	-0.7075	0.5143
	(0.3861)	(0.3220)	(0.4761)	(0.2401)	(0.3038)
(C) RT Expansion vs RT Contraction					
Wald Coeff. Restriction	3.3917+	1.2857		**11.8266****	1.7160
	(0.0682)	(0.2593)		(0.0008)	(0.1929)
Equality of Mean	1.3853+	-0.7808		**2.4780****	-0.9210
	(0.0837)	(0.2179)		(0.0070)	(0.1791)
Wald Coeff. Restriction	2.5982		0.0910	**10.7618****	0.2961
	(0.1098)		(0.7635)	(0.0014)	(0.5874)
Equality of Mean	1.2067		-0.2180	**2.4071****	-0.3841
	(0.1145)		(0.4139)	(0.0085)	(0.3507)
Wald Coeff. Restriction	3.1718+	0.0417	0.5893	**12.2293****	1.3722
	(0.0776)	(0.8385)	(0.4443)	(0.0007)	(0.2439)
Equality of Mean	1.3445+	0.1389	-0.5716	**2.6199****	-0.8330
	(0.0901)	(0.4449)	(0.2841)	(0.0047)	(0.2029)

Notes: Time series of market prices of risk are obtained from cross-section regressions of monthly stock portfolio returns against factor risk sensitivities and run from January 1985 to October 2002. The table reports F-statistics for the Wald test of restrictions to the average price of risk with p-values associated with two-sided alternative hypotheses shown in parentheses. The equality of mean t-statistics test the hypothesis that average prices of risk are equal between two samples, with p-values in parentheses associated with one-sided alternatives. Unequal variances are assumed between samples. **, *, + indicate t-statistics that are statistically significant at the 1, 5 and 10% level of significance. Panel (A) compares real-time average prices of risk with their fully-revised counterparts during months when industrial production was not contracting, Panel (B) conducts identical tests during months when industrial production was contracting and Panel (C) compares real-time average prices of risk during expansions with those during contractions.

Fully-revised macroeconomic data that are currently available and, until now, have conventionally been used in empirical finance research, imply that macroeconomic innovations are not important for the pricing of stocks. More encouragingly, real-time data that measure more accurately the informational flow to the stock market suggests that unexpected inflation and economic uncertainty are important factors for asset pricing. Inflation shocks and a more uncertain investment climate can be interpreted as systematic risk factors that are rewarded by the stock market, which have predictive power over future expected stock returns. Results are therefore very sensitive to the type of macroeconomic data used. Since asset returns respond quickly to economic news surprises, real-time data that allows returns to be matched contemporaneously with economic news releases should be used in financial studies investigating links between financial markets and economic variables.

Pricing relationships are robust to the extraction of the effects of stock market crashes, to different models of economic expectations and the exclusion of the term structure of interest rates on theoretical grounds has been justified by empirical analysis. In an interesting extension of the test, pricing relationships are asymmetric over the business cycle. During periods of economic expansion, inflationary shocks are more prevalent than investment uncertainty and are found to be the sole risk factor influencing expected stock returns. In contrast, when the economy is contracting and the risk of bankruptcies rises, investment uncertainty becomes the most important risk factor for pricing stocks. More generally, the results reported here underscore the importance of using real-time data, which allows returns to be appropriately matched with contemporaneous economic news releases when investigating the links between financial markets and economic variables. Future research might usefully extend our findings by seeking verification of these results in real-time investigations for different asset markets and countries, and might consider alternative factors from a broader set of macroeconomic variables. The use of higher frequency data to isolate the immediate effects of news releases might also be attempted, and alternative approaches to the characterisation of the phase of the business cycle might be employed to further investigate the asymmetric relationship between stock returns and macroeconomic variables over the course of the cycle. The crucial role of unanticipated inflation identified in this study might also prompt further investigation of the links between asset markets and monetary policy.

There are numerous other ways to extend this study by considering the econometrics of the method used to test APT, the modelling of economic expectations and the frequency of the data used in this study. The only potential caveat to the econometric procedure is the possibility that risk factor sensitivities are measured with error. By grouping stocks and using portfolio returns, it is hoped that such an errors-in-variables problem is eliminated. Although Shanken (1992) presents a possible adjustment to account for measurement error, his technique cannot be applied to the rolling regression procedure adopted here. An interesting extension in econometric theory may be able to introduce a method of eliminating measurement errors in estimated factor sensitivities. Similarly, more advanced econometric techniques could be applied to the modelling of economic expectations and the separation of economic expansion and contraction across the business cycle. Further research may also attach more attention to the statistical inference of estimated coefficients rather than to their averages, particularly the estimated sensitivities of risk factors. This may go some way to describing how accurately the specified macroeconomic variables explain stock returns and could highlight the need to identify factors that are as yet undiscovered. There may well be other factors driving stock returns whose pricing influence is more prominent. In addition to improving the econometrics of the study, the impact of news on asset returns may be made clearer by using higher frequency data. A range of factors, other than economic data announcements, could determine monthly stock returns over the course of the month. Analysing the response of returns to real-time economic news with daily or even intraday returns data may uncover more information concerning the importance of macroeconomic news for generating stock returns.

CHAPTER 3

MACROECONOMIC NEWS ANNOUNCEMENT EFFECTS ON THE EURO EXCHANGE RATE

ABSTRACT

Using five-minute returns for spot Euro-Dollar, Euro-Sterling and Euro-Yen exchange rates, this chapter investigates the short-run reaction of Euro returns and volatility to a wide range of macroeconomic announcements. Controlling for the distinct intraday volatility pattern, calendar effects, announcement effects and a latent, longer-run volatility factor simultaneously, the marginal impact of each individual announcement on volatility is isolated. Macroeconomic news announcements from the US are found to cause the vast majority of the statistically significant responses, with monetary policy announcements, real activity and forward looking indicators featuring very prominently. Eurozone interest rate decisions are important for all three rates, whilst UK Industrial Production and Japanese GDP cause large responses for the Euro-Sterling and Euro-Yen rates, respectively. By comparing alternative filters for the intraday volatility pattern, the magnitude of the volatility reaction to announcements is found to be sensitive to the choice of econometric modelling technique, in which context the filters popularly applied in previous studies are found to understate macroeconomic announcement effects. Investigation of the dynamic, short-run response of exchange rate returns to the information surprise of macroeconomic announcements reveals dramatic jumps in conditional returns in response to many US announcements. Moreover, standardised news measures explain staggering proportions of these jumps, showing that exchange rates are strongly linked to fundamentals in the five-minute intervals immediately following the data release.

3.1 INTRODUCTION

The trade-off between risk and expected return is arguably the cornerstone of modern finance. Defined as the variability of the random component of a time series, volatility, and financial market volatility in particular, is not only non-trivial, but is inherently unobservable and evolves stochastically through time, making financial decisions both complicated to analyse in terms of optimisation theory and difficult to implement in practise. The measurement and forecasting of volatility, therefore, are among the most important concepts in empirical finance, with direct implications for asset pricing, portfolio theory and risk management. Volatility has thus become one of the most actively researched areas in time series econometrics and economic forecasting in recent decades. More recently, our understanding, measurement and forecasts of volatility have been advanced tremendously through the availability and application of high frequency financial returns data. Such data is not only important for characterising the real-time trading, pricing and risk management practices used by practitioners in today's liquid financial markets, thus providing an interesting and appropriate structure in which to extend our knowledge of market efficiency and market microstructure, but also provides the closest practical approximation to the continuous-time framework that financial economic theory is founded upon.

The characterisation of the price discovery process, through investigating the way in which news about macroeconomic fundamentals is incorporated into asset prices, lies at the heart of financial economics, and the market efficiency and market microstructure literature in particular. Nowhere is this more important than in the foreign exchange market, where the determination of exchange rates and the link between exchange rates and fundamentals remain the central issues of exchange rate economics. Whilst financial market participants pay close attention to data on underlying economic fundamentals, the apparent difficulty in empirically mapping economic fundamentals to asset prices is remarkable. Indeed, some empirical studies have gone so far as to suggest that exchange rates and fundamentals are largely disconnected, Meese and Rogoff (1983). This conclusion has spurred a substantial literature that has re-examined this issue, but more than twenty years later, the original results have not been convincingly overturned and evidence that fundamentals have predictive content for exchange rate movements remains elusive.[1]

[1] See Mark (1995), Mark and Sul (2001), Berkowitz and Giorgianni (2001), Evans and Lyons (2002) and Faust et al. (2003) for evidence focusing on the foreign exchange market.

The theory of efficient markets contends that financial asset prices should completely and instantaneously reflect public information, implying that price changes should respond quickly to news regarding movements in the underlying economic fundamentals. Despite the apparent lack of predictive power of fundamentals for asset prices, the largest absolute intraday asset returns are closely linked to the release of macroeconomic news. Such spectacular surges in volatility are short-lived and comprise only one component of intraday returns volatility. High frequency data, therefore, are crucial for the analysis of the behaviour of financial markets at the time of public information arrivals, and the major macroeconomic announcements are dominant in the intervals immediately following news releases.[2] However, when considering the data in its entirety, macroeconomic announcement effects are secondary in explaining overall volatility, their explanatory power being lower than both the distinctive intraday volatility pattern at high frequencies and lower than standard volatility forecasts at the daily level. From an econometric perspective, the robust analysis of macroeconomic announcement effects therefore requires the simultaneous modelling of, and control for all three of these volatility factors.

The microstructure of the foreign exchange rate dictates a twenty four hour pattern to intraday volatility governed by trading activity in the world's major financial centres. Volatility increases when trading in the most active centres overlap, whilst the inherent pattern is disrupted by severe spikes immediately following the release of macroeconomic news. The filtration of high frequency returns volatility through modelling of the underlying pattern is essential in order to isolate the true impact effect and dynamic response to news. This involves adopting a deterministic intraday volatility pattern to capture high frequency volatility periodicity, imposing a predetermined volatility response pattern following each news release, and then assessing the extent to which particular announcements load onto this pattern, so allowing the robust and efficient investigation of a wide range of individual announcements. The pioneering work of Andersen and Bollerslev (1998a) provides a robust econometric methodology for capturing the distinct volatility components and

[2] See Ederington and Lee (1993, 1995), Payne (1996), DeGennaro and Shrieves (1997), Almeida et al. (1998), Goodhart et al. (1993), Andersen and Bollerslev (1998a), Chang and Taylor (2003) and Galati and Ho (2003) for evidence on foreign exchange markets; Fleming and Remolona (1999) and Bollerslev et al. (2000), Balduzzi et al. (2001) and Green (2004) for evidence on bond markets and Boyd et al. (2001) and Flannery and Protopapadakis (2002) for evidence on stock markets.

isolating macroeconomic announcement effects. This method has also been applied by Andersen, Bollerslev and Cai (2000) and Bollerslev et al. (2000) to different markets, but very few other studies tackle the complexity involved in the simultaneous modelling of all components of intraday volatility, and many discard valuable information relating to macroeconomic news effects by grouping news events into categories. More recently, studies have used the information surprise of announcements to investigate the immediate behaviour of exchange rates around the releases of data relating to macroeconomic fundamentals. Modelling the dynamics of high frequency returns volatility contributes to a robust econometric methodology for analysing the response of conditional means to news, thus allowing an investigation of the links between macroeconomic fundamentals and asset prices. Andersen, Bollerslev, Diebold and Vega (2003), for example, show that macroeconomic news announcements generate very large, statistically significant, rapid exchange rate movements, characterised as conditional mean jumps. Moreover, news announcements relating to US economic fundamentals explain a massive proportion of these jumps.

This chapter contributes to the literature in several ways. First, it uses five-minute bid-ask quotes of the Euro against the US Dollar, UK Pound sterling and Japanese Yen, which constitutes a new market that has yet to be investigated in this econometric framework. Second, the dataset includes a wide selection of macroeconomic news announcements for the US, Eurozone, Germany, France, UK and Japan to examine whether news regarding relative economic performance impacts upon bilateral exchange rate volatility. Third, the chapter compares two alternative techniques for capturing the intraday volatility pattern, the flexible Fourier form implemented by Andersen and Bollerslev (1998a), Andersen, Bollerslev and Cai (2000) and Bollerslev et al. (2000), and a cubic spline specification advocated by Taylor (2004), which has yet to be applied to foreign exchange data. Fourth, the chapter aims to provide a comprehensive characterisation of Euro volatility focusing on its response to a range of macroeconomic announcements that convey varying degrees of news within a turbulent economic and geopolitical background. The sample is chosen to include a period of global economic recovery following the US recession at the end of 2001, and an unofficial economic slowdown in the summer of 2002 and spring of 2003. The nineteen month sample period also includes episodes of monetary policy easing when the Federal

Reserve, European Central Bank and Bank of England all reduced interest rates, and also covers the beginning of conflict in Iraq. Fifth, using the information surprise elements of news announcements, this chapter also examines the high frequency relationships between exchange rates and macroeconomic fundamentals.

The chapter proceeds as follows. Section 3.2 surveys the important recent literature detailing the component structure to high frequency financial asset returns volatility and focusing on the discovery of intraday volatility patterns, the effects of macroeconomic announcement effects and longer run temporal dependencies. Section 3.3 confirms the presence of such components for intraday Euro volatility, thus motivating the econometric methodology explained in section 3.4, which concentrates on providing an analysis of the magnitude of macroeconomic announcement effects. Section 3.5 presents the results and discussion of both the statistical significance and economic importance of the announcement effects. Section 3.6 utilises the information content of the news releases, relative to expectations, and together with the complex volatility dynamics, in order to perform a robust examination of the short run linkages between exchange rates and macroeconomic fundamentals. Section 3.7 summarises and concludes the chapter and suggests potential avenues for further research.

3.2 LITERATURE REVIEW

One of the most successful innovations in the study of market microstructure and market efficiency over the past twenty years has been the availability and application of high frequency data. This review of that important literature chronicles the development of empirical and theoretical research from early descriptive studies of intraday patterns in returns and returns volatility to more recent analyses that decompose volatility into a number of components and use the vast information in high frequency data to improve volatility forecasting performance. The consistent discovery of distinctive, pervasive patterns in intraday returns volatility across global asset markets, coupled with the importance of volatility for risk management, portfolio allocation and derivatives pricing, has meant that volatility has warranted substantial attention in recent research. In addition to improving our understanding of volatility dynamics, modelling and forecasting, high frequency data are also essential for investigating the short run behaviour of financial markets around macroeconomic news announcements and the dissemination of information into prices.

3.2.1 Intraday Volatility Patterns

The analysis of high frequency data illustrates several interesting features that are inherent to intraday returns volatility and represent econometric issues that require explicit treatment to allow the separation of macroeconomic news announcement effects on volatility. The first of these features is a distinctive intraday volatility pattern, found to be present across all assets. One of the earliest studies using high frequency financial data was conducted by Wood et al. (1985), in their analysis of the behaviour of minute-by-minute US stock returns. By averaging across days within minutes, they construct a return series for what they term a typical trading day. Their key results show that distributions of returns vary during the day and, in particular, the standard deviation of returns is higher at the market open and close, yielding a distinct U shape pattern to volatility. Similarly, using US stock returns measured at the lower frequency of fifteen minutes, Harris (1986) finds systematic intraday returns patterns, where returns are again large at the beginning and end of the trading day. Focusing on the variability of stock returns over a longer sample, McInish and Wood (1990) extend the work of Wood et al. (1985) to confirm a U-shape pattern in volatility. Lockwood and Linn (1990) also study US stock returns, but at the hourly frequency, and also find that returns volatility is higher at the market open and close.

Attempts to prove that this intraday pattern in volatility is neither sample nor market specific have inspired empiricists to investigate alternative asset markets. Derivatives markets have received particular attention because high frequency data has allowed authors to re-examine finer lead-lag relationships, causality between spot and futures markets and connections between implied and historical volatility in options markets. A striking feature of this literature is the repeated discovery of U-shaped intraday volatility patterns. The important early studies include Kawaller et al. (1990), Ekman (1992) and Lee and Lin (1994), all of whom analyse S&P 500 Index futures. Kawaller et al. (1994) replicate the patterns when using options on S&P 500 Index futures, Eurodollar futures and live cattle futures and, Daigler (1997) also finds U-shaped intraday volatility in S&P 500, MMI and Treasury bond futures.[3]

[3] Further international evidence of U shaped intraday volatility in futures markets includes Tse (1999) for FTSE 100 Index futures, ap Gwilym et al. (1999) for FTSE 100 Index, Short Sterling and Long Gilt futures and Ballocchi et al. (1999) for Eurofutures.

There are two competing theories that explain why volatility should be higher when markets open and close. The 'asymmetric information' model proposed by Admati and Pfleiderer (1988) suggests that patterns in volume and price variability emerge as the consequence of the interaction and strategic decisions of information and liquidity traders. Information and liquidity are two widely recognised motives for trading in financial markets. Information traders trade on the basis of private information unknown to other traders at the time of their trades, while liquidity traders trade for reasons determined outside the market such as the liquidity needs of clients or portfolio rebalancing reasons. Admati and Pfleiderer (1988) assume the existence of discretionary liquidity traders who time their trades to minimise the expected cost of their transaction. They therefore prefer to trade during periods when their trading has little effect on prices and this creates an incentive for all liquidity trading to be concentrated. Given that information traders are in competition with each other, they also prefer to trade when the market is thick, in order to avoid signalling their private information to other traders, and therefore trade more actively in periods when liquidity trading is concentrated. Since liquidity demand is highest at the market opening and closing, these intervals exhibit concentrations of liquidity and informed trading causing higher volume and more variable returns.

A competing model proposed by Brock and Kleidon (1992) extends Merton's (1971) continuous trading model to show that the liquidity demand from traders rebalancing their portfolios before and after market closures creates U-shaped patterns in volume and volatility. Brock and Kleidon (1992) name their model a 'market maker power theory' since market makers take advantage of the increased liquidity demand as markets open and close to widen bid-ask spreads. The theory is also known as a 'market closure model' because it is founded on the impact that non-trading periods have on trading preferences, meaning that opening and closing periods are the precise reason for the concentration of volume and the cause of higher volatility. More specifically, exogenous changes in demand for transactions at the open and close drive the trading patterns, rather than the endogenous changes in demand employed by information models. There are many potential reasons for exogenous trading demand to occur at the open and close, including: portfolio rebalancing due to the change from a closed market to continuous trading and vice versa; information arrival overnight and a greater divergence of opinion among traders at the beginning of the day; and the closure or hedging of open trading positions.

The foreign exchange market deserves special note because it is the largest financial market in the world by volume, and provides the focus of this study. The decentralisation of the market across regional financial centres and disparate time zones permits continuous trading, which offers an interesting arena in which to develop and test market microstructure theories. Baillie and Bollerslev (1990) examine hourly exchange rates for four major spot rates: the British Pound (GBP), Deutsche Mark (DEM), Swiss Franc (CHF) and Japanese Yen (JPY), all against the US Dollar (USD).[4] They find that patterns in volatility appear to be related to the opening and closing of the world's major markets in East Asia, Europe and the US with a striking increase in volatility observed for all currencies (including bilateral cross-rates not involving USD), around the opening of markets in London and New York.

In a statistical study of three years of intraday data on four spot foreign exchange rates against USD, Müller et al. (1990) confirm the evidence of Baillie and Bollerslev (1990) that the foreign exchange market is a twenty-four hour market and must be treated as such. Intraday volatility patterns, they suggest, are distinctly uneven, but can be explained by the behaviour of the three main markets, East Asia, Europe and the US, whose active periods partially overlap. Such systematic variations in volatility are observed within trading days, which Dacorogna et al. (1993) propose can be explained by using simple geographical assumptions about the presence of traders in the market. They argue that seasonal volatility patterns can be modelled by introducing a new variable termed activity, which differs between markets and exchange rates to reflect the specific interest of each geographical region in particular currencies.

Using the DEM-USD exchange rate, Bollerslev and Domowitz (1993) examine international intraday trading activity and the time series properties of returns and bid-ask spreads. They confirm earlier evidence that trading activity is elevated when global financial centres are open, and is at its highest when trading in disparate centres overlap. Using GMT as local time, Bollerslev and Domowitz (1993) show that trading activity picks up after midnight as Tokyo and Sydney markets open,

---

[4] Three letter currency codes refer to ISO conventions.

and is followed by the start of trading in Singapore and Hong Kong. Activity declines sharply as trading is suspended for the Tokyo lunch period and then increases during the afternoon trading session in the Far East, until Hong Kong and Singapore close and London and Frankfurt open.[5] A decline in activity is then observed during the European lunch period until the opening in New York. Activity is at its highest when New York and European markets overlap, declining after the close of European trading centres and again after the close of New York until the Far East opens again. More recently, identical intraday patterns have been found for returns volatility in the DEM-USD exchange rate by Andersen and Bollerslev (1997a, 1997b, 1998a), who characterise volatility as the sum of two overlapping U-shapes in the Far East and Europe and an inverted U-shape for the US segment of the market.

Evidence of U-shaped volatility patterns in asset markets is presented consistently in studies using high frequency data. In the most recent literature, Cai et al. (2004) use one-minute observations to document a U shaped pattern for returns volatility for all securities traded on the London Stock Exchange. Using five-minute data to analyse market volatility in the Dow Jones Industrial Average in the presence of trading collars, Aradhyula and Ergün (2004) support a U-shaped intraday periodicity in volatility. Cyree et al. (2004) examine hourly observations of one-month Eurodollar time deposit rates to find an intraday volatility pattern where volatility clusters at the beginning and end of the regular business day. Bauwens et al. (2005) confirm the distinctive twenty four hour volatility pattern in the FX market by analysing five-minute EUR-USD returns. These studies reinforce the importance, robustness and regularity of intraday volatility patterns across global markets and all financial instruments. Their presence is widely and frequently noted, with more recent attention in the empirical finance literature now devoted to the explicit econometric modelling of such patterns for the purpose of understanding the components driving returns volatility, with a particular view towards improving volatility forecasting.

---

[5] Regulations restricting trading by Tokyo banks between 12:00 and 13:30 Tokyo time were lifted on December 22nd 1994. See Ito et al. (1998) and Andersen, Bollerslev and Das (1998) for an examination of the effects on intraday volatility from this liberation.

3.2.2 Macroeconomic News Announcement Effects

Many studies have documented periods of elevated volatility or volatility spikes, which correspond exactly to the release of macroeconomic news.[6] Although a relatively recent phenomenon in the study of intraday volatility, the effects of the arrival of public information in financial markets have been a popular area of research for some time and are important for understanding market microstructure and market efficiency. An important early study is that conducted by Hardouvelis (1988) who examines the response of exchange rates and interest rates to the new information contained in the first announcement of fifteen US macroeconomic series. Markets are found to respond primarily to monetary news, but also to news about the trade deficit, inflation and variables that reflect the state of the business cycle. Focusing on volatility, Harvey and Huang (1991) analyse the foreign currency futures market and confirm that volatility increases at times that coincide with the release of US macroeconomic news.

Extending this early work, Ederington and Lee (1993) provide a more detailed analysis of market responses in their widely cited study examining the impact of scheduled macroeconomic news announcements on Treasury Bond, Eurodollar and DEM-USD futures. They argue that intraday and interday volatility patterns in these markets are due to the timing of macroeconomic news releases, with the Employment Report, Producer Price Index (PPI), Consumer Price Index (CPI) and Durable Goods orders showing the greatest impact on interest rate futures, (in order of declining impact), while the Employment Report, Trade Deficit, PPI, Durable Goods orders, GNP and Retail Sales have the largest impact on currency futures. Furthermore, Ederington and Lee (1993) show that the bulk of the price adjustment to a macroeconomic news announcement occurs within the first minute of the release and that volatility remains substantially higher than normal for fifteen minutes and slightly elevated for several hours after the announcement. Contrary to research on equity markets, Ederington and Lee (1993) find no volatility spike at the opening of the futures markets they analyse, suggesting that the spike observed at US equity market openings is caused by the macroeconomic news released just prior to their opening.

[6] See for example Becker et al. (1993), Andersen and Bollerslev (1997b, 1998a), Daigler (1997) Tse (1999), Docking et al. (1999) and ap Gwilym et al. (1999).

The findings of Ederington and Lee (1993) have sparked tremendous interest in the short run response of financial markets to the announcement of public information, and macroeconomic news in particular. Goodhart et al. (1993), for example, investigate the impact of two isolated news announcements on the GBP-USD exchange rate: namely, better than expected US Trade figures, and a percentage point rise in UK base interest rates. They conclude that these news effects influence both the level and uncertainty of exchange rates, but not permanently. Jones et al. (1994) provide evidence that public information is a major source of short term stock return volatility. In an extension to their seminal paper, Ederington and Lee (1995) re-examine the immediate adjustment of prices in interest rate and exchange rate futures markets to new information contained in macroeconomic news releases by using ultra high frequency data. They suggest that prices adjust in a series of numerous, small but rapid, price changes that begin ten seconds after the release and are completed within forty seconds. Also, they find no evidence of information leakage, that is the leakage of macroeconomic news just prior to the official release time, despite higher volatility being observed just before announcements.

With particular relevance to the foreign exchange market, Payne (1996) analyses the DEM-USD exchange rate and reports large volatility impacts associated with the release of the Employment Report and Trade figures. Markets are found to quieten in anticipation of news releases, but after the release there is a pronounced and persistent impact on volatility. DeGennaro and Shrieves (1997) investigate the USD-JPY rate and conclude that news releases affect volatility levels and are important determinants of exchange rate volatility. The DEM-USD rate is also the subject of work by Almeida et al. (1998), who identify significant impacts of most macroeconomic news announcements within fifteen minutes of the release. The strong, quick impact of macroeconomic news on the exchange rate reflects the anticipated policy reaction by monetary authorities to the piece of news just released, showing that the foreign exchange market's primary concern is with the future likely reaction of the monetary authorities. News from German announcements is found to be incorporated more slowly due to differences in the timing and scheduling arrangements of announcements between Germany and the US, and DEM-USD volatility is found to be driven more by US than German announcements, the strength of the latter depending on the proximity of the release to the next Bundesbank council meeting. In related work studying bond markets, Jones et al.

(1998) find that employment and PPI news releases are associated with substantial bond market volatility, yet announcement day volatility does not persist, consistent with the immediate incorporation of information into prices. Fleming and Remolona (1999) discover a two stage adjustment process for prices, volume and spreads in the US Treasury market in response to public information, and Balduzzi et al. (2001) document significant and persistent increases in volatility and trading volume after scheduled macroeconomic announcements. For stock markets, Flannery and Protopapadakis (2002) find news of three nominal factors (CPI, PPI and a monetary aggregate) and three real factors (the Trade Balance, Employment Report and Housing Starts) to cause important reactions in volatility. Chang and Taylor (2003) investigate the DEM-USD exchange rate and find that US and German macroeconomic news and German Bundesbank monetary policy news all have a significant impact on intraday DEM-USD volatility.

In more recent work on the foreign exchange market, Andersen, Bollerslev, Diebold and Vega (2003) characterise the conditional means of five US dollar spot exchange rates and find that announcement surprises produce conditional mean jumps; hence, high-frequency exchange rate dynamics are linked to fundamentals. The details of the linkages, they suggest, are intriguing and include announcement timing and asymmetric sign effects. In an extension of this work, Andersen, Bollerslev, Diebold and Vega (2007) show that US news surprises cause conditional mean jumps in high frequency US, German and British stock, bond and foreign exchange markets. Furthermore, they show that equity markets react differently to the same news depending on the state of the economy over the business cycle, with bad news having a positive impact during expansions and the traditionally expected negative impact during recessions. Also focusing on the conditional mean, Ehrmann and Fratzscher (2005) analyse the link between economic fundamentals and exchange rates by investigating the importance of real-time data. They find that economic news in the US, Germany and Eurozone have been a driving force behind daily USD-DEM developments, with US news having the largest influence, particularly in periods of large market uncertainty and when negative or large shocks occur. Evans and Lyons (2005) investigate whether macroeconomic news arrivals affect trading in currency markets over time, finding that news arrivals induce changes in trading behaviour that remain significant for days and have persistent effects on prices, thus currency markets do not respond to news instantaneously. In one of the very few known studies of the Euro since EMU, Galati and Ho (2003) present a preliminary investigation of the extent to which daily movements in the EUR-USD rate were driven by the macroeconomic situation in the US and Eurozone area. A number of findings emerge: first, macroeconomic news is found to have a statistically significant correlation with daily movements of EUR against USD; second, there is asymmetry in the response to news, both geographic and in terms of the type of news; third, the impact of macroeconomic news is stronger when the sign of the news is switched; and fourth, there is considerable time variation in the response of the EUR-USD exchange rate.

The asymmetric response of the daily EUR-USD exchange rate to macroeconomic and political news, depending on whether it emanates from the US or Eurozone and whether it is good or bad news, is confirmed by Prast and de Vor (2005). Sager and Taylor (2004) implement higher frequency data and concentrate on the impact of European Central Bank Governing Council interest rate announcements, finding strong evidence that the policy announcements contain significant news content. Jansen and De Haan (2005) also focus on the ECB, but expand their coverage to include statements and not just policy announcements. ECB statements are found to mainly influence the daily conditional volatility of the EUR-USD exchange rate with some evidence of asymmetric reactions to news. Finally, Bauwens et al. (2005) study the impact of nine categories of scheduled and unscheduled news announcements on high-frequency EUR-USD volatility. Volatility is found to increase in the pre-announcement periods, particularly before scheduled events, but, surprisingly there is very little evidence of a reaction during the post-announcement periods. It is this very recent literature that this chapter expands upon in order to identify the nature and details of linkages between news about macroeconomic fundamentals and exchange rate volatility, by analysing high frequency data and concentrating on the contribution of individual announcements to volatility.

3.2.3 Long Run Persistence and Temporal Aggregation

In addition to intraday volatility patterns and spikes corresponding to the release of macroeconomic news, other prevalent features of asset returns, include fat tailed distributions and volatility clustering, where large (small) returns tend to be followed by large (small) returns of either sign. The Autoregressive Conditional

Heteroscedasticity (ARCH) model proposed by Engle (1982) and the Generalised ARCH (GARCH) framework introduced by Bollerslev (1986) provide popular techniques for the empirical modelling of volatility in financial time series since they readily accommodate these stylised characteristics of asset returns.[7] A common result of these early applications of these methods finds that the conditional volatility processes are nearly integrated, meaning that shocks to daily volatility persist indefinitely. More recent research, however, argues that this long run dependence is more appropriately characterised by slowly, mean-reverting, fractionally integrated processes, such that shocks to volatility are highly persistent but eventually dissipate.[8] The use of high frequency returns data when estimating standard GARCH models by Guillaume et al. (1995), Dacorogna et al. (1997), Müller et al. (1997) and Andersen and Bollerslev (1997a), however, show that coefficient estimates deviate from their theoretical values, based on the temporal aggregation of GARCH processes. Specifically, Nelson (1990a, 1990b, 1991, 1992), Drost and Nijman (1993) and Drost and Werker (1996) argue that volatility persistence in GARCH processes, measured as the sum of parameter coefficients, should increase at higher frequencies, whereas empirical studies appear to show lower persistence at the intraday than the interday frequencies. Theories attempting to explain the conflicting results at the intraday and interday frequencies suggest that volatility may be decomposed into heterogeneous components with different dependence structures.

The long memory property of asset returns volatility may also be a manifestation of structural breaks in the data series and this issue has received considerable attention in the recent literature in order to improve volatility modelling and forecasting techniques. Franses et al. (2002), for example, compare the modelling and forecasting performance of a model that specifically describes and forecasts the location and size of level shifts with a long memory model which is known to pick up neglected level shifts. Andreou and Ghysels (2002) evaluate the performance of tests for structural breaks in the conditional variance dynamics of asset returns, where these statistics identify the number and location of multiple breaks. Further evidence that occasional structural breaks generate slowly decaying autocorrelations and other properties of fractionally integrated processes is provided

[7] See Bollerslev et al. (1992), Bera and Higgins (1993) and Bollerslev et al. (1994) for reviews of applications of these models to data at daily or lower frequencies.
[8] See for example Ding et al. (1993), Ding and Granger (1996), Granger and Ding (1996), Baillie et al. (1996) and Bollerslev and Mikkelsen (1996).

by Granger and Hyung (2004) who also show that at least part of the long memory may be caused by the presence of neglected breaks in the series. Finally, Morana and Beltratti (2004) test for the existence of long memory and structural breaks in the realised volatility process for the DEM-USD and USD-JPY exchange rates. They find that whilst long memory is evident in the actual processes, a structural break analysis reveals that this long memory feature is partially explained by changes in regime. Furthermore, they suggest that neglecting the break process is not important for very short term forecasting, but superior forecasts can be obtained at longer horizons by modelling both long memory and structural change.

3.2.4 Volatility Components

Much of the recent work on high frequency asset return volatility stems from a series of seminal papers by Andersen and Bollerslev (1997a, 1997b, 1998a) that identify a component structure to high frequency returns volatility and justify the stylised patterns found by introducing a theory of public information arrival. The culmination of this series of papers demonstrates the importance of considering these components jointly rather than in isolation. Firstly, Andersen and Bollerslev (1997a) propose a general methodology for the extraction of the intraday periodic component of return volatility and show the importance of this procedure in the DEM-USD exchange rate and S&P 500 index futures contract returns. They replicate the common U-shape intraday volatility patterns for equity index futures and the distinctive twenty-four hour pattern for intraday DEM-USD returns volatility, and also reveal striking regularities in the autocorrelation patterns of absolute returns. As well as strong U-shaped intraday patterns, autocorrelations at the daily frequency show a strong cyclical pattern, and decay slowly over the first four days only to increase slightly at the weekly frequency, signalling a minor day-of-the-week effect. The combination of recurring cycles at the daily frequency and a slow decay in the autocorrelations can be explained by the joint presence of the pronounced intraday periodicity and strongly persistent daily conditional heteroscedasticity, highlighting two components of volatility. Andersen and Bollerslev (1997a) show that the presence of the intraday periodic component of volatility causes serious misspecifications of GARCH models, prompting them to introduce a general method of estimating and extracting the intraday periodicity. Filtration of absolute returns by an intraday periodicity component, estimated by a Fourier flexible functional form, and standardisation by an estimated daily GARCH component to account for persistence at lower frequencies, reveals interesting patterns in the correlogram of absolute returns that are invisible prior to the periodic filtering.[9] Any remaining observed correlation patterns, Andersen and Bollerslev (1997a) suggest, may be caused by the arrival of public information such as macroeconomic news, representing the third volatility component.

In the second paper of the series, Andersen and Bollerslev (1997b) formulate a version of the mixture-of-distributions hypothesis (MDH) for returns that accommodates numerous heterogeneous information arrival processes, in order to explain the existence of long-run volatility persistence and multiple volatility components in high frequency returns. Using five-minute DEM-USD returns and conducting a low-pass filter of returns, Andersen and Bollerslev (1997b) extract the strong intraday patterns so as to leave all the low frequency information that pertains to the interdaily frequencies. This direct analysis of the volatility persistence from the high frequency data supports the notion of long-memory dependence as an inherent feature of the return generating process, and illustrates the usefulness of the filtered series for direct analysis of the longer run volatility implications of macroeconomic announcements.[10] Andersen and Bollerslev (1997b) extend the MDH such that not only are information flows not constant over time, but may also derive from heterogeneous processes. Volatility in this case may be interpreted as a mixture of numerous heterogeneous information arrival processes, some with very short run decay rates and others possessing much longer dependencies. Aggregate volatility

[9] There are alternative methods available for estimating the intraday periodicity to use in this standardisation. Andersen and Bollerslev (1997a) use the mean volatility for a particular interval averaged across days, Gençay et al. (2001) use a method based on a wavelet multi-scaling approach, Aradhyula and Ergün (2004) capture intraday seasonality with a third order polynomial specification and Taylor (2004) employs a more sophisticated cubic spline approach.

[10] The MDH, originally formulated by Clark (1973), suggests that asset prices be modelled as a subordinate stochastic process evolving at different rates according to the flow of information during identical time intervals, with prices evolving faster when unexpected information flows into the market. Since the flow of information which causes prices to move is not constant over time, neither is the variance of returns, suggesting that the distribution of returns is a mixture of normals with changing variance. Epps and Epps (1976) also suggest that returns can be viewed as following a mixture of distributions, but with transactions volume as the mixing variable rather than unexpected information flows. They argue that information causes traders to change their reservation prices and the greater the disagreement between traders, the greater the level of trading volume. This implies a causal link between information, volume and return variability. Copeland (1976) and Jennings et al. (1981) assume new information is disseminated to traders sequentially to propose alternative hypotheses for the existence of a positive volatility-volume relationship. Tauchen and Pitts (1983) also show that the joint distribution of daily price changes and volume can be modelled by a mixture of bivariate normal distributions.

will then contain both short and long run components, the former dominating over intraday frequencies and the latter over lower frequencies. After extracting the short run intraday volatility patterns by filtering, Andersen and Bollerslev (1997b) show that volatility in the DEM-USD exchange rate exhibits identical long run dependence irrespective of sampling frequency. Long run dependence is therefore an inherent component of returns volatility, which can be uncovered in relatively short intervals of high frequency data by first annihilating the intraday periodicity in time series of intraday returns.

In the final paper of this series, Andersen and Bollerslev (1998a) combine the techniques used in the first two papers to model the intraday periodicity and long run dependence found in DEM-USD returns and isolate macroeconomic news as the remaining component of volatility in order to discuss the relative importance of each of the components at different frequencies. The main findings are as follows. First, the largest absolute returns are linked to the release of public information, and more specifically to certain macroeconomic news. However, although the announcements dominate immediately after the release, their explanatory power is low compared to the other components. High frequency returns are crucial for identifying the news that impacts the market, but the spectacular responses of prices are short lived and are not the driving factor of volatility, the most important component being standard volatility forecasts at the daily frequency, while the next most important is the intraday pattern at high frequency. Second, Andersen and Bollerslev (1998a) find that US news regarding the real economy are the most significant news releases, including the Employment Report, Trade Balance and Durable Goods orders, while the most important German announcements are monetary, namely Bundesbank meetings and M3 Money Supply figures. Third, the clustering of public information releases on certain weekdays explains the day-of-the-week effect that volatility tends to be higher towards the end of the week. Fourth, the significant calendar effects include a distinct intraday volatility pattern, reflecting activity in regional centres, as well as strong holiday, weekend, Daylight Savings Time, and Tokyo market opening effects. Fifth, standard daily ARCH effects are found in a short sample of high frequency intraday returns, the presence of long memory characteristics in high frequency returns indicating that this characteristic is intrinsic to the returns generating process and not a result of exogenous shocks.

The recent empirical research using high frequency data has confirmed the presence of the volatility components suggested by Andersen and Bollerslev (1997a, 1997b, 1998a) and has attempted to disentangle the competing theories underpinning their existence. Speight et al. (2000), for example, report evidence for volatility decomposition in intraday FTSE-100 futures returns. Furthermore, they offer empirical support for the heterogeneous information arrival MDH interpretation at all but the higher frequencies, but suggest that the component volatility structure at higher frequencies is more likely attributable to traders with very short time horizons as advocated by Müller et al. (1997).[11] Bollerslev et al. (2000) separate volatility components in the US Treasury bond market. Regularly scheduled macroeconomic announcements are an important source of volatility at the intraday level, with the Humphrey-Hawkins testimony, the Employment Report, PPI, Employment Costs, Retail Sales and the National Association of Purchasing Managers (NAPM) Index having the greatest impact. Bollerslev et al. (2000) also uncover striking long memory volatility dependencies in the fixed income market. Andersen, Bollerslev and Cai (2000) characterise volatility in the Japanese stock market in a similar fashion. Again, they identify strong intraday patterns and interday persistence in five minute Nikkei 225 returns, but find that Japanese macroeconomic news releases are of limited importance with only some announcements having significant short term impact on volatility. Further evidence of multiple sources of volatility is supplied by McMillan and Speight (2006, 2007) for a range of dollar exchange rates and FTSE 100 index futures. In the only known study of this type for EUR-USD, Bauwens et al. (2005) analyse the impact of nine categories of news on high frequency EUR-USD volatility, filtered by the average intraday volatility pattern, in the framework of ARCH models. This chapter applies more robust techniques for filtering the intraday volatility pattern and analysing the dynamic volatility response to macroeconomic announcements to high frequency EUR-USD volatility in order to determine which individual news announcements are influential.

[11] The theoretical foundation underlying this decomposition of volatility into components is the heterogeneous information arrival version of the mixture of distributions hypothesis. Müller et al. (1997), however, propose an alternative that suggests that volatilities of different time resolutions behave differently because of heterogeneous agents rather than heterogeneous information flows. Specifically, market participants under this paradigm have different time horizons, such that short term traders evaluate the market at a higher frequency and have shorter memory than long term traders. These diverse traders follow different investment strategies depending on their objectives, perception of the market, risk profiles and information.

3.2.5 Volatility Forecasting

Given the importance of returns volatility for asset pricing, portfolio allocation and risk management, the precise estimation and forecasting of volatility in financial markets is crucial. Accurate measures and forecasts are essential for the implementation and evaluation of asset and derivative pricing models and trading and hedging strategies. Volatility forecasting can be traced to early applications of the ARCH and GARCH framework introduced by Engle (1982) and Bollerslev (1986), respectively, as the first econometric technique able to explicitly model the temporal dependencies which are observed in returns volatility as clustering. There has been a resurgence of this literature recently, making use of the important informational content of intraday returns, as identified through the successful modelling of the heterogeneous components of financial market volatility, in order to provide improved volatility forecasts. Moreover, academics have also recently revived the GARCH class of models, in contradiction of the early criticism of their forecasting performance, finding that they are able to forecast volatility with greater accuracy when researchers use high frequency data and correctly specify the true 'realised volatility' measure against which forecasting performance should be measured. This sub-section reviews these developments in the literature in more detail.

Despite the early empirical success of the GARCH model and its subsequent versions in modelling the volatility of asset prices in-sample, these models have been subjected to criticism regarding their out-of-sample forecasting performance.[12] For example, Tse (1991) and Tse and Tung (1992) show that an exponentially weighted moving average model is superior to the GARCH model in terms of forecasting performance for the Japanese and Singapore stock markets, respectively. Guillaume et al. (1995) argue that the out-of-sample predictive power of GARCH for the volatility of various exchange rates against USD is found to be lower than that of historical volatility. Considering options on currency futures, Jorion (1995) shows that simple moving average and GARCH models are outperformed by volatility forecasts implied from option prices. Franses and van Dijk (1996) provide evidence to support a random walk model over non-linear GARCH variants for stock markets in Germany, Netherlands, Italy, Spain and Sweden. More recently, Vilasuso (2002)

[12] See survey papers by Bera and Higgins (1993) and Bollerslev et al. (1992).

shows that substantial gains in forecasting accuracy can be achieved with a fractionally integrated model compared to a GARCH model. Further evidence of the poor forecasting performance is shown by Cumby et al. (1993), West and Cho (1995), Figlewski (1997) and Jorion (1996).

In most studies applying GARCH models to capture the intertemporal dependence in asset return volatility, empiricists commonly find that coefficient estimates suggest a high degree of volatility persistence. The studies listed above, however, find that although the parameters are highly significant in sample, the models explain little of the variability in ex-post volatility as measured by the squared or absolute returns over the relevant forecast horizon. These findings have led to the perception that GARCH volatility forecasts may be of little practical use. Contrary to this view, Andersen and Bollerslev (1998b) demonstrate that well-specified GARCH models yield surprisingly accurate volatility forecasts. The apparent poor predictive power of GARCH models when judged against squared returns as the measure of volatility, they suggest, is a consequence of the inherent noise in the return generating process. Although squared returns are a model free, unbiased estimator for the latent volatility factor, they contain a large idiosyncratic component that is unrelated to the actual volatility driving the market. By using cumulative squared returns from high frequency intraday data, which asymptotically reduces the measurement error involved in measuring ex- post volatility as the sampling intervals become finer and building on the continuous-time stochastic volatility framework of Nelson (1990b) and Drost and Werker (1996), Andersen and Bollerslev (1998b) construct a more accurate ex-post volatility measure, which they call 'integrated volatility'. When evaluated under this more appropriate setting, which corresponds to notions of volatility derived from diffusion models (Barndorff-Nielsen and Shephard, 1998) and consistent with volatility measures emphasised in the stochastic volatility option pricing literature (Hull and White, 1987), they find that the forecasting performance of GARCH models is substantially improved.

Integrated volatility, derived from continuous-time diffusion models, is a measure of the true latent volatility; however, it is unobservable in practice since financial data can only be sampled at discrete intervals. 'Realised volatility', measured as the sum of finely sampled intraday squared returns, represents the best practical measure of this latent volatility. Andersen, Bollerslev and Lange (1999) use a ten-year sample of five-minute DEM-USD returns to show that standard volatility models provide good forecasts of this economically relevant realised volatility measure over a range of forecasting horizons from short intraday to one month intervals. In light of this, Andersen, Bollerslev and Lange (1999) provide a clear motivation for explicitly incorporating the information in high frequency returns to produce substantially improved forecasting performance. In developing a true measure of volatility against which forecasts should be measured, Andersen, Bollerslev, Diebold and Labys (2003) present a general framework for the inclusion of high frequency intraday data into the measurement, modelling and forecasting of daily and lower frequency volatility and return distributions. They calculate realised volatility as the sum of squared intraday returns, which is an unbiased ex post estimator of daily return volatility that is asymptotically free of measurement error, meaning that it becomes a more accurate measure of realised volatility the finer the sampling frequency of the intraday data used in its construction. This concept reinforces the importance of extracting the information held in high frequency data and encourages its use in developing improved forecasting models. As the result of such an important discovery in financial economics, the theoretical and empirical literature examining realised volatility and its use in constructing improved volatility forecasts is expanding rapidly. In particular, Barndorff-Nielsen and Shephard (2002a), Meddahi (2002, 2003), Andersen, Bollerslev, Diebold and Labys (2003) and Andersen, Bollerslev and Diebold (2007a) have made significant contributions to the econometric theory of realised volatility; Andersen, Bollerslev, Diebold and Ebens (2001) and Andersen, Bollerslev, Diebold and Labys (2001a,b) have concentrated on the distribution of realised volatility; and Andersen, Bollerslev, Diebold and Labys (2003) and Andersen, Bollerslev and Meddahi (2004, 2005) have advanced the use of high frequency data and realised volatilities for forecasting improvements.

In addition, within the context of volatility forecasting, Martens (2001) investigates whether intraday returns contain important information for forecasting daily volatility. In particular, Martens (2001) investigates whether the direct modelling of intraday returns provides better out-of-sample forecasts for daily volatility, evaluated using realised volatility. Daily volatility forecasts constructed from multiple volatility forecasts for intraday intervals are shown to provide superior forecasts for daily volatility for DEM-USD and USD-JPY. Furthermore, Martens (2001) concludes that the higher the frequency used, the better the out of sample daily volatility forecasts. By measuring ex-post volatility using a new algorithm based on Fourier analysis, Barucci and Reno (2002) find that the forecasting performance of GARCH models is improved and this is shown by using high frequency DEM-USD and USD-JPY returns. Further support in favour of GARCH models is provided by McMillan and Speight (2004) who find that GARCH models provide superior volatility forecasts of seventeen daily exchange rates as compared to smoothing and moving average techniques, when evaluating forecasting performance against realised volatility.

3.3 VOLATILITY COMPONENTS

3.3.1 Data

The foreign exchange market is characterised by the publication of bid and ask quotes by market makers, generally bank traders, representing the prices at which they stand ready to buy and sell foreign currency, respectively. The market makers also contribute this information to organisations that disseminate financial information globally. This study utilises such inter-bank bid-ask quotes for Euro-Dollar (EUR-USD), Euro-Sterling (EUR-GBP) and Euro-Yen (EUR-JPY) spot exchange rates that have been provided by Olsen Data.[13] Bid and ask quotes were collected at five-minute intervals from 21:00 GMT on 1st January 2002 to 21:00 GMT on 31st July 2003.[14] The data represent the last quotes during a particular five-minute interval, thus avoiding the problem of linear interpolation, and intervals that do not contain any quotes are assigned the same quote as the previous interval. The logarithmic price, $\log(P_{t,n})$, is defined as the mid-point of the logarithmic bid and ask. Since trading in the FX market is continuous and trading activity in the world's major financial centres overlap, the trading day is twenty four hours long beginning at 21:00 GMT to capture the opening of trading in Sydney and Asia and continuing until 21:00 GMT the following day to include the close of trading in the US.[15] This produces 288 five-minute intervals during the day. To avoid confounding the data by the inclusion of slower trading periods over weekends, quotes form Friday 21:00 GMT to Sunday 21:00 GMT were removed by Olsen Data.[16] The *n*th return within

[13] www.olsen.ch

[14] 1st January 2002 is excluded at the outset since it is a public holiday in all of the major global financial centres.

[15] To demonstrate this it is possible to assign subjective trading hours to each trading centre: Wellington, 20:00 to 4:00; Sydney 21:00 to 6:00; Tokyo, 00:00 to 8:00; Europe, 6:00 to 15:00; London, 7:00 to 16:00 and US, 11:30 to 20:30.

[16] See Bollerslev and Domowitz (1993) for a justification of this weekend definition.

day t ($R_{t,n}$) is calculated as the change in logarithmic prices during the corresponding period where $t=1, 2... T$ references the trading day and $n=1, 2... N$ represents the intraday interval, with $T=412$ and $N=288$ so the sample contains $TN=118,656$ five-minute returns for each exchange rate.

The sample includes all public holidays, which present an empirical dilemma. Quoting activity on these days is so low that the calculated returns are rendered unreliable and so they should be excluded from the sample, yet, it is important to maintain a continuous-time series when investigating the strict intraday periodicity of asset markets. Days during which quoting activity is so low as to render returns unreliable are classified as market closures, and five-minute returns during these intervals are assigned an artificially low, positive return. Specifically, these periods are 20:30 GMT on 28th March 2002 to 21:00 GMT on 1st April 2002 (Easter); 19:00 GMT on 24th December 2002 to 00:00 GMT on 26th December 2002 (Christmas); 20:30 GMT on 31st December 2002 to 22:00 GMT on 1st January 2003 (New Year's Day) and 20:30 GMT on 17th April 2003 to 21:00 GMT on 21st April 2003 (Easter). In addition, there are some days in the sample during which quoting activity during parts of trading day is low due to regional public holidays, yet activity is sufficient to deem the calculated returns to be reliable and so they are maintained in the sample. Regional holidays affect only a small segment of the trading day and the overlap of trading in different locations ensures that returns are reliable even if activity is low.[17] The effect of these regional holidays on volatility is controlled for explicitly in the econometric framework of section 3.4.

Care must also be taken when dealing with weekend returns and gaps in the time series, caused by a break in the data feed, so as not to introduce any influences into intraday volatility that may be caused by events occurring outside standard trading hours.[18] Since weekend quotes between 21:00 GMT on Friday and 21:00

[17] The regional holidays are Martin Luther King's Day, President's Day, Memorial Day, Independence Day, Labour Day, Columbus Day, Veteran's Day and Thanksgiving for the US; Early May Bank Holiday, HM Queen Elizabeth II's Golden Jubilee (3rd June 2002), Spring Bank Holiday and Summer Bank holiday for the UK; 2nd and 3rd January, Coming of Age Day, Founding of the Nation Day, Start of Spring (Vernal Equinox), Day of Nature, Constitution Day, Children's Day, Navy Day, Respect for the Aged Day, Fall Equinox, Physical Fitness Day, National Culture Day, Labour Thanksgiving Day, Emperor's Birthday and 31st December for Japan; Australia Day, Anzac Day, Queen's Birthday and Labour Day in Australia and Wellington public holiday, Queen's Birthday and Labour Day for New Zealand.

[18] Although trading in FX markets is continuous, trading activity is dominated by banks acting on behalf of their clients or their proprietary accounts. This means that most trading activity is confined to the business hours when these banks are open.

GMT on Sunday are removed by Olsen Data, the first return calculated on a Monday morning measures the difference between prices on Friday 21:00 GMT and Sunday 21:05 GMT. This return is likely to reflect information related to geopolitical events gathered on days when the world's major trading centres are closed. However, closer inspection of the data reveals that there are often gaps in the data on Monday morning, which manifest themselves as long series of zero returns. These episodes give rise to a large return at 21:05 GMT on Monday which reflects the difference between the price at the Friday close and the stale price generated by the gap in the data and this tends to be followed by another large return of the opposite sign once the data feed is restored. Following Andersen and Bollerslev (1998a), these episodes of missing data are treated as market closures and assigned an artificially low, positive return so as not to disrupt any underlying periodicities of intraday volatility.

The sample means of the five-minute returns for EUR-USD, EUR-GBP and EUR-JPY of 0.000218%, 0.000124% and 0.000124% are indistinguishable from zero at standard significance levels given sample standard deviations of 0.037997%, 0.034451% and 0.038007%, respectively. Returns are clearly not normally distributed, with sample skewness calculated as -0.008483, 0.304071 and 0.125412, and sample kurtosis measured as 9.831, 22.509 and 15.191, which are all highly significant.[19] The first order autocorrelations of -0.08, -0.19 and -0.11 for each currency pair are highly significant because of the large sample size, but they are small in economic terms. These small negative statistics provide some support for the hypothesis that foreign exchange dealers position their quotes asymmetrically relative to the perceived true market price as a way to manage their inventory positions, thus causing the mid-point of the quoted prices to move in a similar fashion to the 'bid-ask bounce' commonly observed on organised exchanges.

The data set also includes information concerning important macroeconomic announcements in the US, Europe, the UK and Japan, which has been provided by Money Market Services International. This information includes the actual data released and its exact timing to the nearest minute.

The remainder of this section presents evidence that supports the existence of three factors driving return volatility: a distinctive intraday pattern; macroeconomic news announcement effects; and long run dependencies. The discovery of these three

[19] The standard errors of these statistics in their corresponding asymptotic normal distributions are $(6/T)^{1/2}$ and $(24/T)^{1/2}$ (see Andersen and Bollerslev, 1997a).

components provides the motivation and foundation for the explicit volatility modelling procedure that accounts for each component simultaneously in order to isolate the impulse impact and dynamic response of Euro volatility to macroeconomic news announcements.

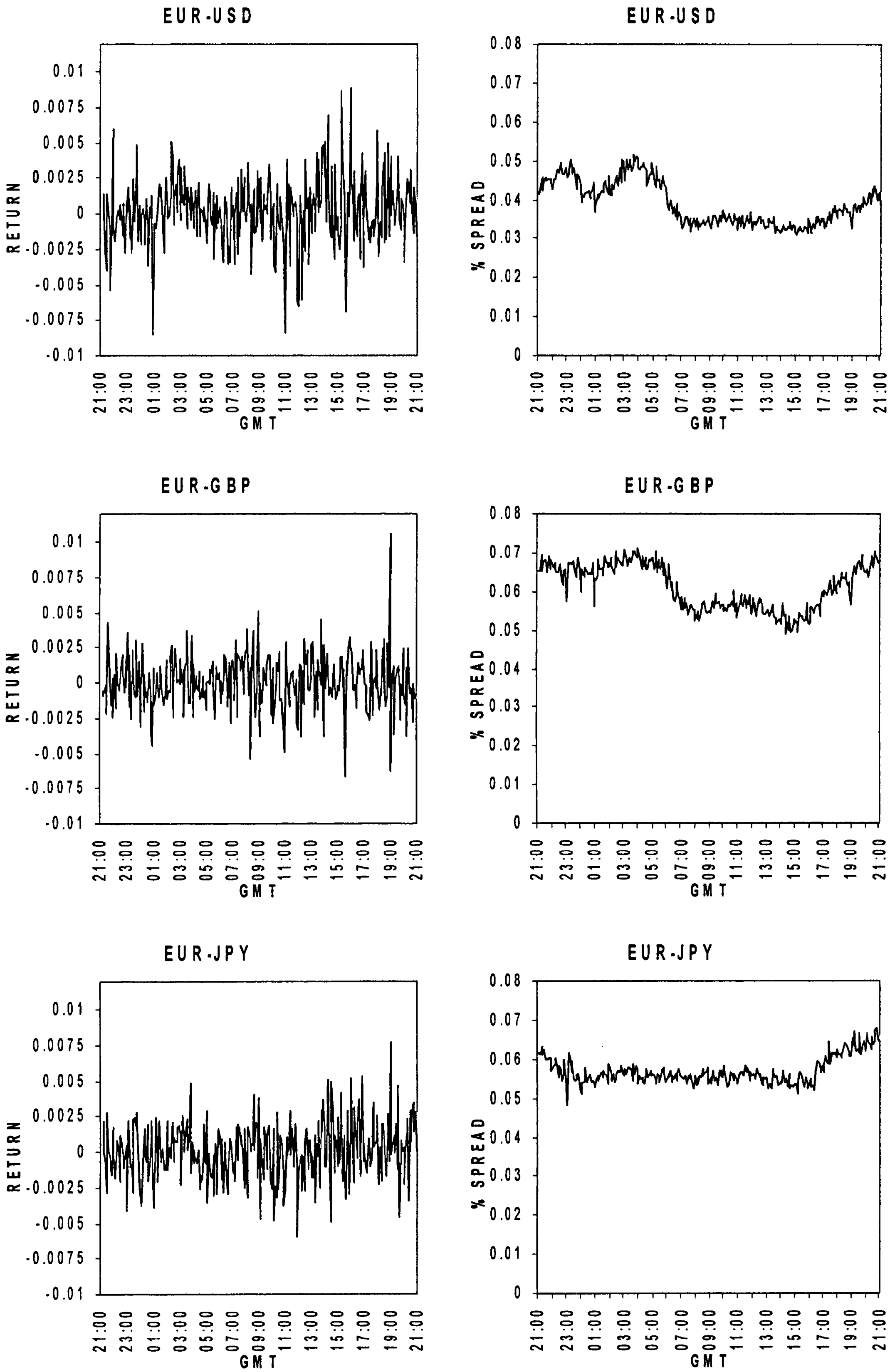
3.3.2 Intraday Patterns in Returns and Spreads

In order to analyse intraday patterns in returns, the left hand column of Figure 3.3.2.1 shows the plots of returns averaged across days within intraday intervals. Across the three currency pairs there are interesting similarities between the plots, but no discernible systematic patterns in average intraday returns. Over the course of a trading day, returns tend to fluctuate around zero with wider fluctuations indicating periods of higher volatility. Volatility appears to be higher for EUR-USD than EUR-JPY, which, in turn, is higher than that for EUR-GBP. The timing of increases in volatility, however, reveals that patterns in volatility may be evident.

The right hand column of Figure 3.3.2.1 shows intraday patterns for the bid-ask spread for each currency pair, calculated as a percentage of the mid-point price. The percentage spread is lowest for EUR-USD, reflecting the fact that this is the most heavily traded and therefore most liquid of the three currency pairs. There is a U-shaped pattern corresponding to the Asian trading session indicating wider bid-ask spreads at the opening and closing of Asian trading, followed by a sharp decline at the start of trading in Europe from 5:00 GMT. The most active trading centres are Europe and the US, and when they overlap EUR-USD trading is at its most liquid, explaining why the percentage bid-ask spreads are at their lowest values from 11:00 GMT to 15:00 GMT. Spreads then begin to widen as liquidity declines at the close of US trading in readiness for the opening of trading in Australia and New Zealand.

The percentage spread is higher for EUR-GBP than EUR-USD. Trading volume and liquidity are relatively lower which means there is less competition for business between market makers allowing them to increase profits by widening spreads. There exists a U-shape pattern for the percentage spread for the Asian trading session, although this is much shallower than for EUR-USD. As with EUR-USD, there is a sharp narrowing of EUR-GBP spreads when European trading opens and yet further narrowing when European and US trading sessions overlap. Towards the close of trading in the US, EUR-GBP spreads widen again showing the fall in liquidity.

Figure 3.3.2.1. Intraday Patterns for Returns and Percentage Spreads.



Finally, the intraday percentage spread pattern for EUR-JPY lies below that for EUR-GBP and above that for EUR-USD. Following a narrowing of spreads after the opening of trading in Sydney, the pattern is much flatter than for the other two currencies until spreads widen at the close of trading in the US.

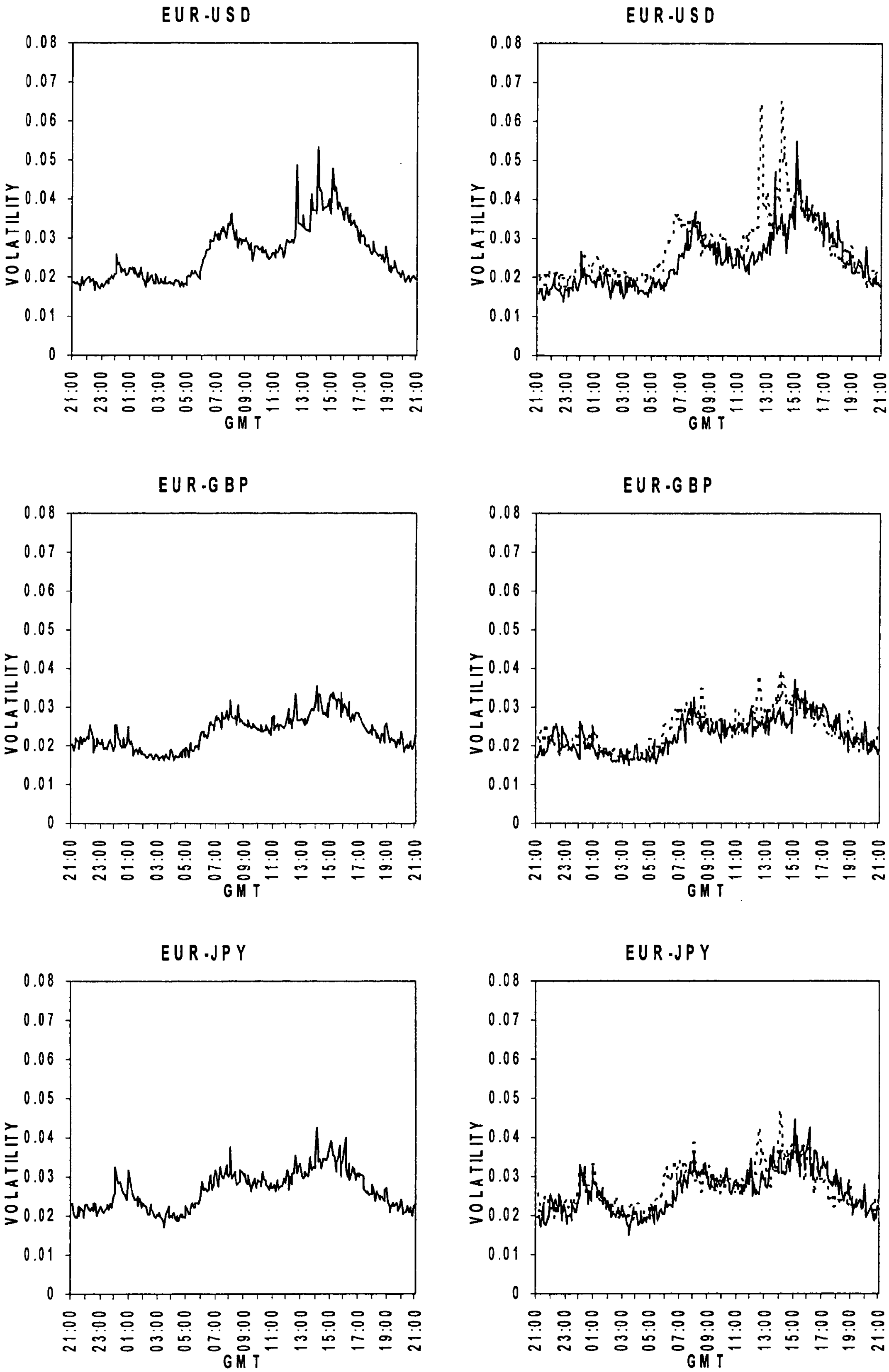
3.3.3 Intraday Volatility Patterns

The fluctuations of returns shown in the left hand column of Figure 3.3.2.1 reveal that volatility increases as the trading day progresses with particular episodes of high volatility corresponding to the opening and overlapping of trading in Asia, Europe and the US. These systematic patterns are more clearly identified in the plots in Figure 3.3.3.1. The first column shows plots of average five-minute absolute returns against intraday interval for each currency. [20] Intraday volatility patterns are strikingly similar in all three graphs and confirm the evidence presented previously by Bollerslev and Domowitz (1993), Dacorogna et al. (1993) and Andersen and Bollerslev (1997a, 1997b and 1998a).Two important findings from these graphs are, firstly, a distinctive twenty-four hour pattern to exchange rate volatility, determined by the opening of trading in the major global financial centres and periods where trading activity in these centres overlaps and, secondly, the interruption of this pattern by volatility spikes which follow immediately the announcement of macroeconomic news.

Volatility for each exchange rate begins the day at around 0.02%, then jumps as stock, bond and derivative markets open in Tokyo at 00:00 GMT. Following an increase in volatility at the start of trading in Japan, there is another jump as markets open in Hong Kong, Singapore and Malaysia, an effect which is particularly noticeable for EUR-JPY and EUR-GBP. Volatility then declines to its lowest level of the day at approximately 4:00 GMT, before rising to another distinct peak at 8:00 GMT, which corresponds to an overlap between the close of trading in East Asia and the early activity of traders in Europe and the UK. Volatility shows a distinct U-shape pattern for the Asian trading session, with the peak at the opening of the European trading session noticeably higher than at the opening of the Japanese session.

[20] There are alternative measures of volatility that could be used, including squared returns, standard deviation of returns and the logarithm of squared returns. The analysis in the section is corroborated by different volatility measures, but in accordance with recent literature and for brevity, only the absolute return is reported here.

Figure 3.3.3.1. Intraday Volatility Patterns.



From the peak at 8:00 GMT, volatility declines to another trough before rising again when trading in Europe overlaps with early trading activity in the US, confirming the second intraday U-shape of the day for the European session. The bow of this U-shape occurs at approximately 11:30 GMT, volatility then rising as trading activity increases in readiness for the opening of US markets to reach a peak for the day at approximately 15:00 GMT. The timing of this peak corresponds to the interaction of the most active financial centres in the world and regular releases of US macroeconomic news. After this peak, volatility declines slowly as US markets close for the day before traders in Sydney begin trading for another day. To demonstrate the extent of volatility fluctuations at the intraday level and to show the impact these intraday calendar effects have for trading, risk management and portfolio allocation strategies, the range between the highest intraday volatility peak and lowest trough are calculated. These ranges, measured as a percentage of the lowest absolute five-minute return, are 220%, 115% and 149% for EUR-USD, EUR-GBP and EUR-JPY, respectively, showing massive fluctuations for average intraday volatility and the importance of this feature as a component of volatility.

The plots in the first column of Figure 3.3.3.1 confirm the familiar empirical findings for high frequency foreign exchange data: a distinctive twenty-four hour pattern for intraday volatility; higher volatility in periods when trading activities in more than one financial centre overlap, and no direct evidence of heightened volatility at regional market closures. Allowing for the continuous trading of the foreign exchange market, intraday volatility can be characterised by two U-shapes for the Asian and European trading sessions, where the peaks in volatility occur at times when trading in disparate financial centres overlap. Another interesting feature of these results is that for each U-shape the right-hand peak is higher than the left-hand peak, which can be more accurately described as an asymmetric U-shape and is caused by the overlap between more active financial centres as the day progresses. With no obvious peaks in volatility at the close of trading in London and New York, there is no direct evidence of heightened volatility at the close of trading, which is in contrast to previous findings for stock, bond and derivatives markets that operate under strict opening hours.

3.3.4 Intraday Volatility Patterns for Daylight Saving Time

Although GMT is a universal time convention, it is not the most accurate way of measuring intraday intervals because trading activity and return volatility are determined by the local time in geographic regions, which may alter relative to GMT when Europe and the US switch to Daylight Saving Time (DST). Averaging volatility across days for all days in the sample therefore implies averaging within two different intervals in terms of local time, separated by one hour.[21] To ensure that volatility is averaged within the same intraday interval when measured by local time and to provide a more precise description of the timing of the intraday patterns, the sample is separated into winter time and DST. DST runs from the last weekend in March to the last weekend in October, during which period European and US clocks are moved forward by one hour relative to GMT. Separating the sample into these two seasons gives 239 trading days during DST and 173 days during winter time. Intraday volatility patterns for DST and winter time are shown in the plots in the right hand column of Figure 3.3.3.1, DST shown by the dotted line and winter time shown by the solid line in all cases.

DST is not adopted in Japan, so it is not surprising that the Asian trading session is unaffected by this separation of the sample. Although clocks are altered in Sydney and Wellington in the opposite direction to the northern hemisphere, volatility is relatively low during their trading sessions and there is no discernible change to volatility patterns during this early part of the day. The European and US trading sessions, however, show a significant change in the intraday pattern where the pattern for DST shifts to the left by precisely one hour. EUR-USD volatility increases with the increase in activity in Europe at 4:00 GMT in DST but at 5:00 GMT in winter, both times corresponding to 6:00 in Europe. The peak of the European U shape occurs at 7:00 GMT in DST and 8:00 GMT in winter, which always corresponds to 9:00 in Europe and 8:00 in London, showing a surge in volatility when European and UK trading sessions open and overlap. The low point of the U shape during the European session occurs at 11:30 GMT in DST and 12:30 GMT in winter, corresponding to 13:30 in Europe, 12:30 in London and 7:30 in the morning in New York. As activity picks up in the US from this time, volatility rises

[21] For example, the 5 minute interval ending at 15:00 GMT corresponds to 16:00 in Europe, 15:00 in the UK and 10:00 in the US during winter timing conventions, but relates to 17:00 in Europe, 16:00 in the UK and 11:00 in the US when Europe, the UK and the US adopt DST.

to its highest point of the day just after 14:00 GMT in DST and 15:00 GMT in winter, which translate to 16:00 in Europe, 15:00 in London and 10:00 in New York. There is then a steady decline in volatility up to 21:00 GMT. This separation of the sample demonstrates that the timing of the U-shaped volatility curves during different geographical trading sessions corresponds precisely to overlapping periods of trading, which occur at exactly the same time of day when measured in local time. As shown by Figure 3.3.3.1, the peaks of the U-shapes increase throughout the day culminating during the overlap between Europe and the US, the most active financial centres in the world. It is also important to note that volatility during the US session is remarkably higher for EUR-USD than the other two currency pairs, which is entirely as expected given that active investors and traders during this session pay most attention to trading their domestic currency.

Another important finding is the identical timing of the intraday volatility peaks and troughs between the three currency pairs. Levels of volatility during particular trading sessions, however, do vary between exchange rates. Since all three rates represent the price of the Euro, it is not surprising that the European trading session displays a similar level of volatility regardless of which currency it is traded against. Similar to the effect of US investors on EUR-USD during the US trading session, volatility during the Asian session is higher for EUR-JPY than for the other two exchange rates, further illustrating the focus given to the domestic currency during a particular region's trading session. Fluctuations of volatility between peaks and troughs are again substantial, calculated as 315% and 215% during winter and DST periods for EUR-USD, 145% and 144% for winter and DST periods for EUR-GBP and 192% and 154% for the respective periods for EUR-JPY.

3.3.5 Intraday Volatility by Weekday

As a robustness check and to identify weekly volatility effects, figures 3.3.5.1 to 3.3.5.3 illustrate volatility patterns calculated by weekday.[22] The intraday volatility plots for EUR-USD show a remarkably similar pattern across all weekdays with identical timings of peaks and troughs of U-shapes, and volatility is noticeably lower on Monday mornings and late on Friday evenings.

[22] The plots show that the sample is not separated by DST and winter time in order to conserve a sufficient number of days when averaging volatility. A leftward shift of the pattern by precisely one hour is observed if this separation is performed.

Figure 3.3.5.1. EUR-USD Intraday Volatility Patterns by Weekday.

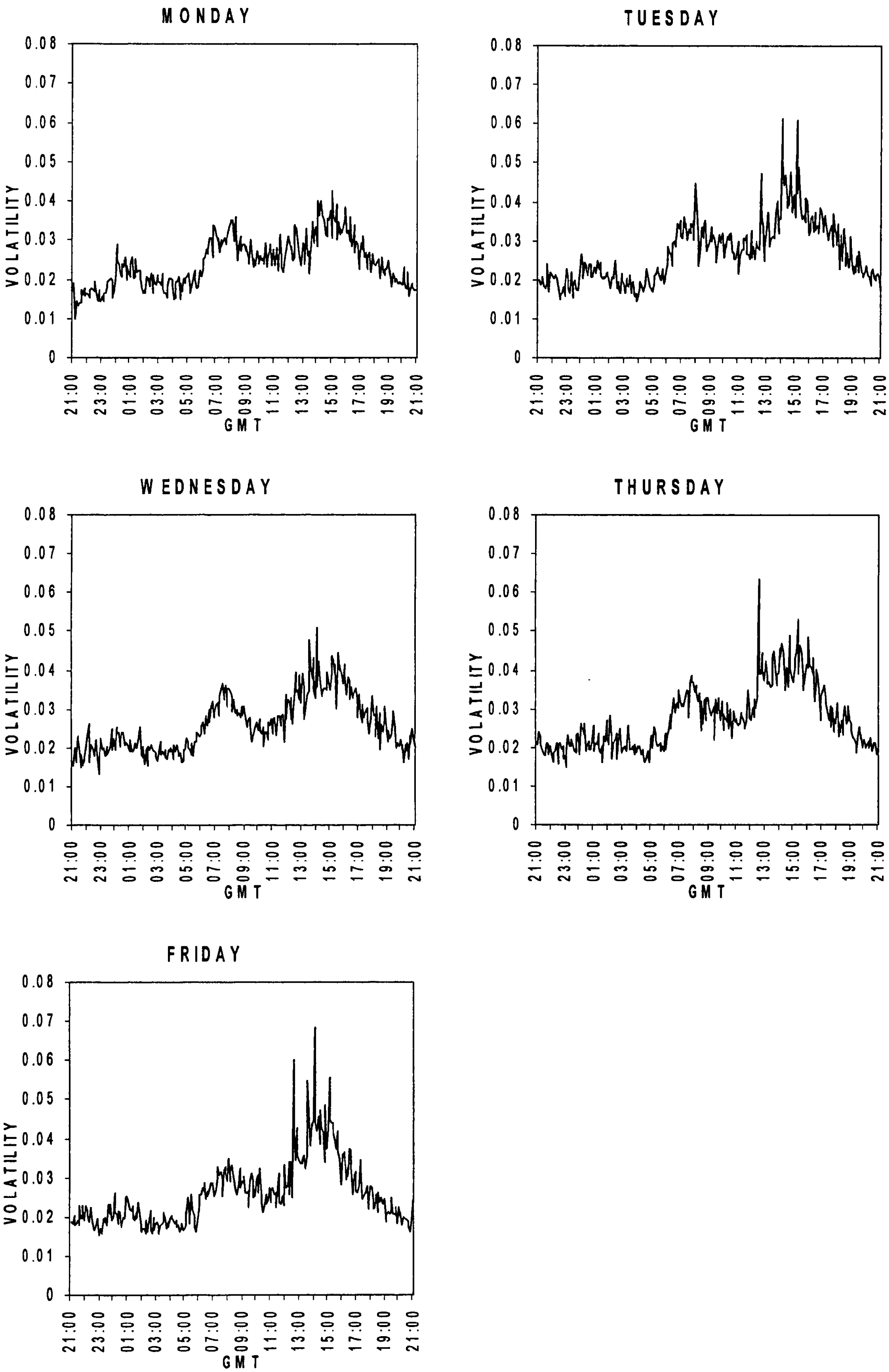


Figure 3.3.5.2. EUR-GBP Intraday Volatility Patterns by Weekday.

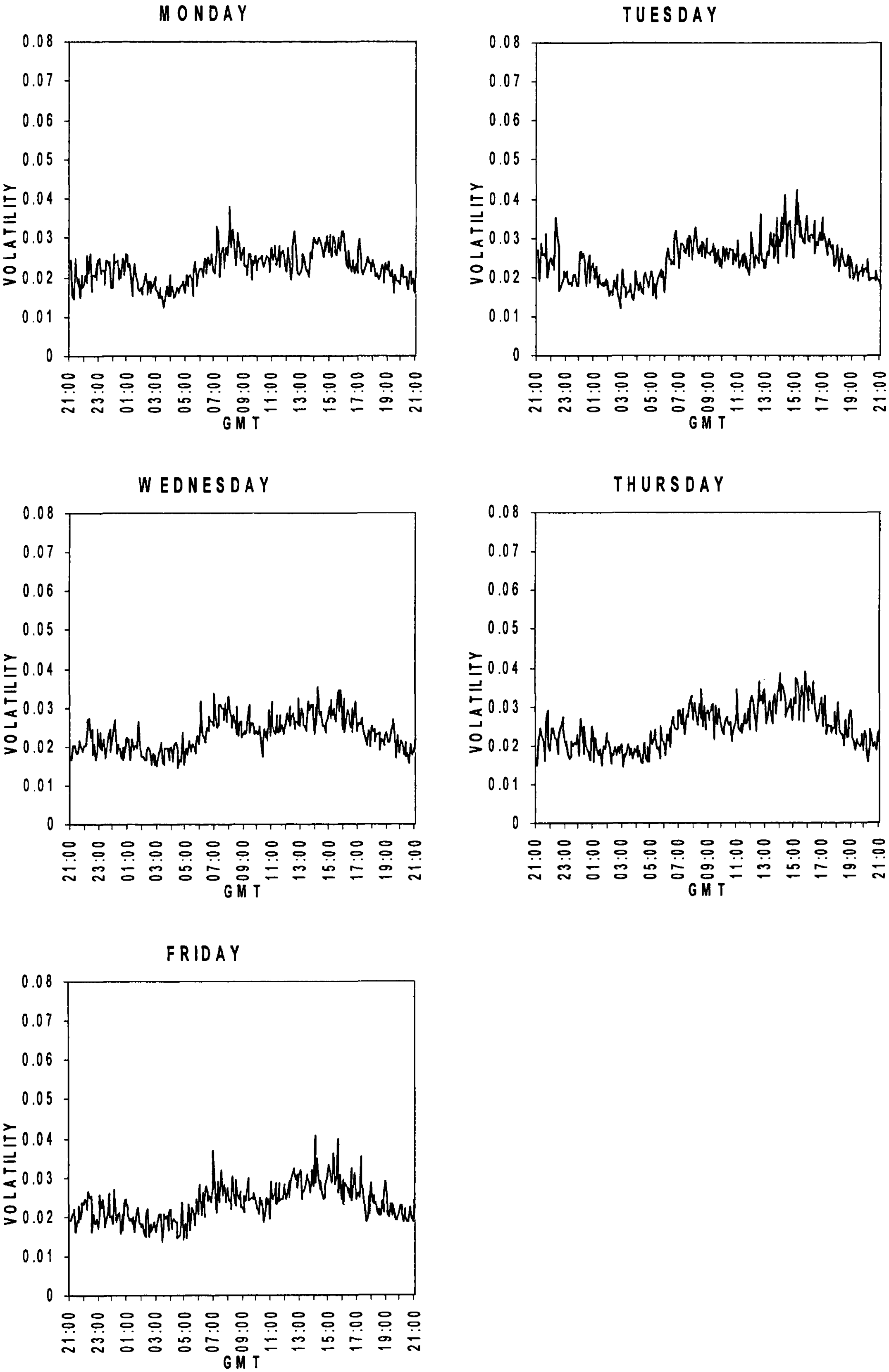
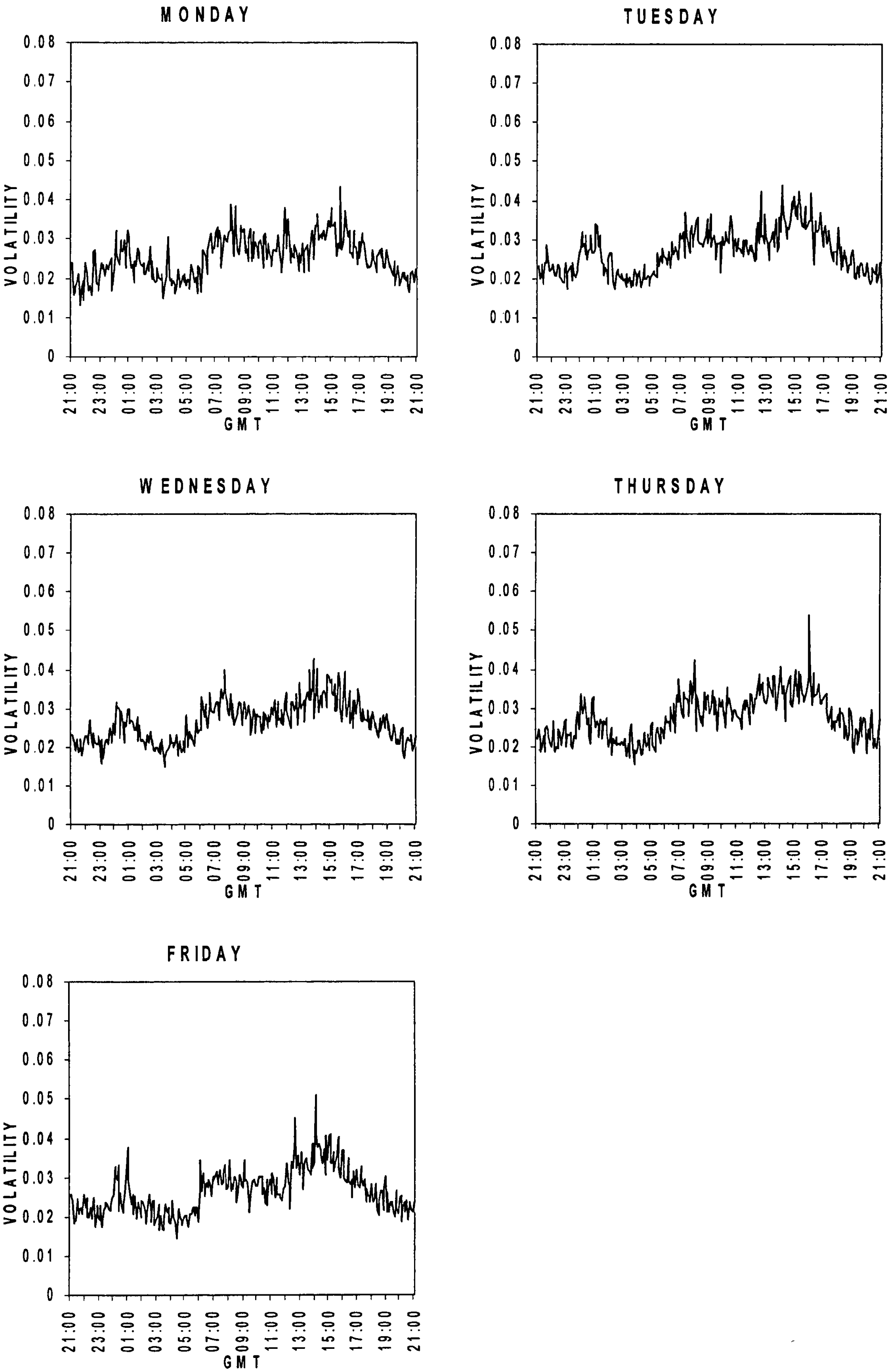


Figure 3.3.5.3. EUR-JPY Intraday Volatility Patterns by Weekday.

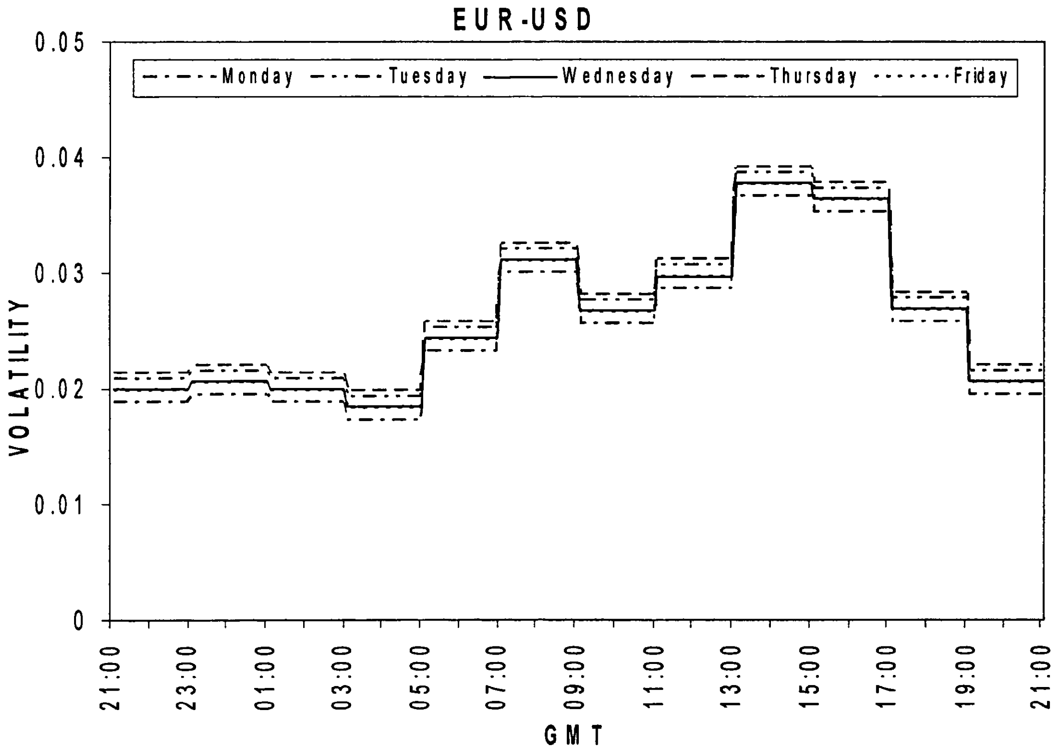


These distinctive patterns are disrupted by severe spikes which correspond exactly to the announcement of macroeconomic news. Interestingly, the severity of these spikes varies between days depending on the regularity of scheduled news releases and the type of data revealed, and a more detailed discussion of these effects follows in later sections. Intraday volatility patterns for EUR-GBP also reveal an identical shape and timing across weekdays. Volatility is generally low on Monday mornings, but this is interspersed with minor spikes as traders accumulate information over the weekend. There exists remarkably lower volatility during the US trading session for EUR-GBP for all weekdays and Wednesdays and Thursdays in particular. The most pronounced spikes of any weekday occurs during the interval immediately after the release of US macroeconomic news, but these spikes are much smaller than for EUR-USD volatility.

Finally, the evidence for intraday volatility patterns is further supported by the plots for EUR-JPY intraday volatility by weekday shown in Figure 3.3.5.3. The precise timing of the U-shapes is identical across weekdays and exactly the same as for the other two exchange rates. However, the opening of markets in Tokyo at 00:00 GMT, and in Hong Kong, Singapore and Malaysia at 1:00 GMT, cause much more dramatic increases in volatility for EUR-JPY than the other two currencies. The volatility peak at 00.00 GMT, reflecting the opening of markets in Tokyo, is almost as high as the peak caused by early trading in Europe, showing a U-shape that is very close to being symmetrical, and is evident on all weekdays. As expected, the US trading session displays lower volatility for EUR-GBP and EUR-JPY than the corresponding plots for EUR-USD, but the Asian trading session shows higher EUR-JPY volatility than for the other currencies. There is also evidence of a volatility slowdown for EUR-JPY on Monday mornings. The intraday pattern for EUR-JPY is also disrupted by volatility spikes, the largest of which occur during the US trading session caused by regularly scheduled US macroeconomic announcements.

Finally, Figure 3.3.5.4 displays the estimated average absolute returns obtained from a regression on two-hour and day of the week dummies. The plots confirm the intraday volatility pattern and reveal clear day of the week dependencies in the high frequency returns. Consistently across the three currencies, Tuesdays and Thursdays are the most volatile and Mondays are the least volatile.

Figure 3.3.5.4. Intraday and Daily Volatility Patterns.



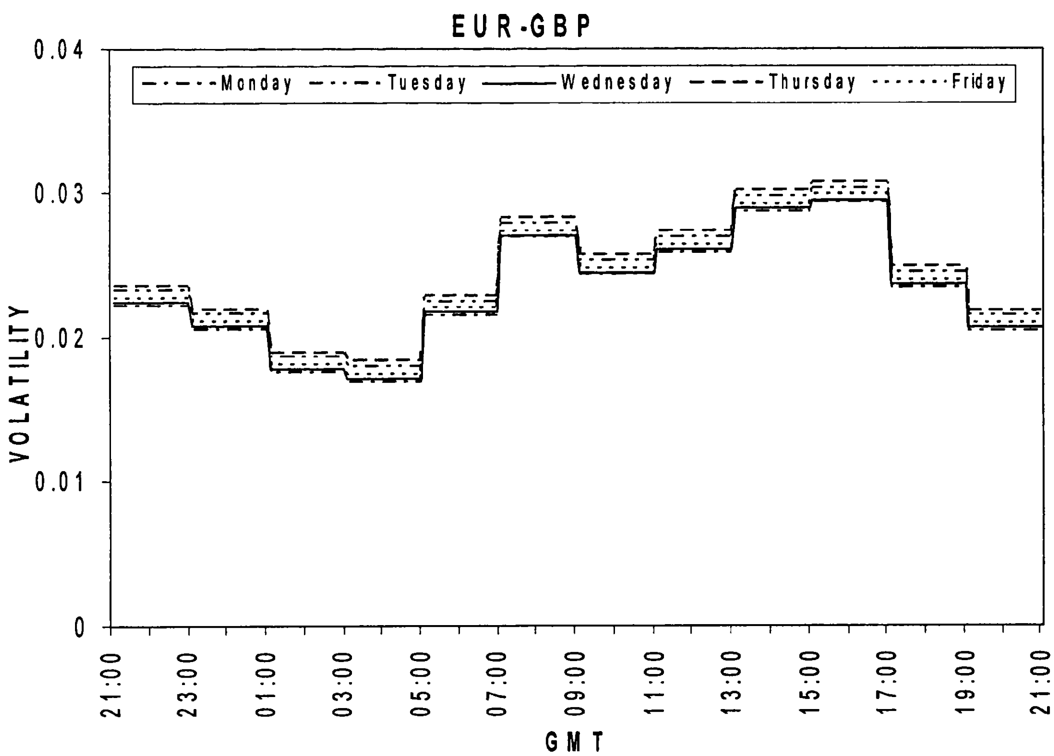
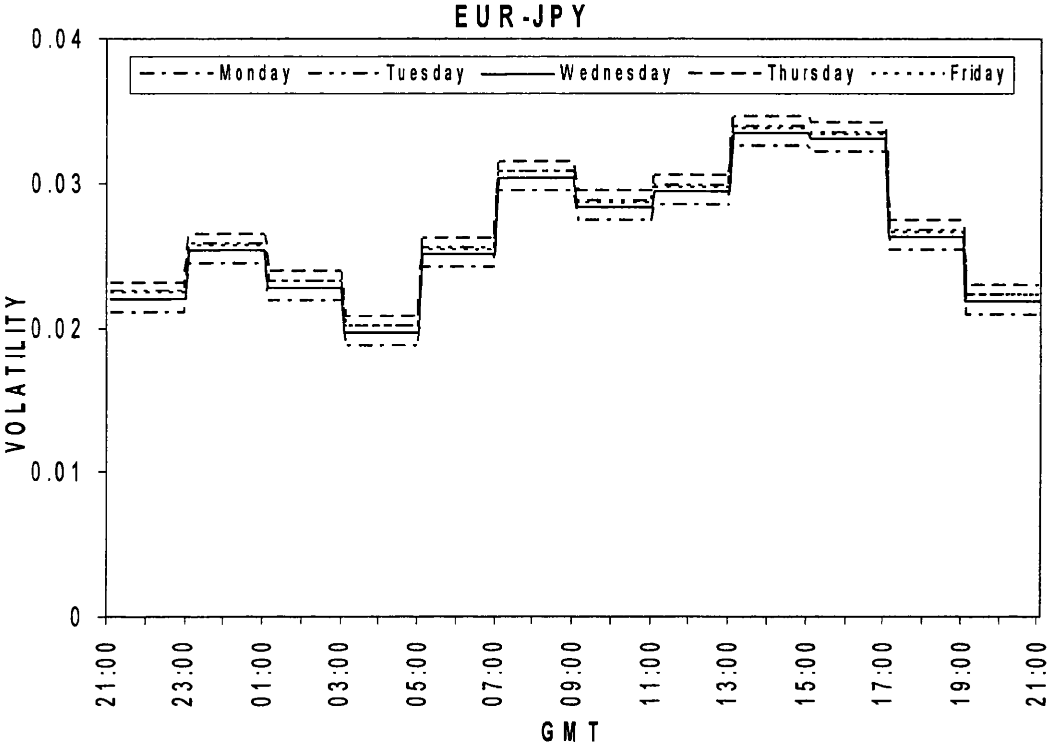


Figure 3.3.5.4. (Continued)



3.3.6 Macroeconomic Announcement Effects

Two very prominent findings have emerged from the preliminary data analysis. First, there exists a clear twenty-four hour pattern to average intraday volatility. Volatility heightens at the opening of markets in the world's major financial centres, beginning with Wellington and Sydney and followed closely by Tokyo and then Hong Kong, Singapore and Malaysia, after which peaks in volatility become progressively higher as the more active centres of Europe, London and the US begin their trading days. Periods when trading overlaps between regions is characterised by peaks of characteristic U-shapes joining to form the distinctive intraday pattern. Not only are these patterns identical across the three EUR exchange rates, but the timing of the peaks, troughs and spikes in intraday volatility are identical. Moreover, the patterns are more pronounced when separating European and US winter time and DST periods, showing that volatility patterns are determined by, and more accurately measured by, local time in the regional centres rather than GMT. The pattern is also robust to the separation of the sample according to weekdays; however, its level is higher on Tuesdays and Thursdays than other weekdays.

The second important discovery of the preceding analysis is the interruption of this pattern by severe volatility spikes that correspond precisely to intervals immediately following the announcement of macroeconomic news. The first plot in the first column of Figure 3.3.3.1, for example, shows clear spikes for EUR-USD volatility during the intervals ending at 12:35, 13:35, 14:05 and 15:05 GMT. These times correspond exactly with regularly scheduled announcements of US macroeconomic indicators, which occur at 8:30 and 10:00 Eastern Standard Time (EST).[23] Although difficult to see clearly from the plots, volatility appears to remain elevated for at least thirty minutes after the announcement. Volatility spikes are less extreme for EUR-GBP and EUR-JPY than EUR-USD, making it more difficult to separate them from the underlying intraday patterns. By separating the sample into winter and DST periods, a more accurate measurement of average volatility according to local time produces a clearer intraday pattern and more distinct volatility spikes as shown by the second column of Figure 3.3.3.1. For EUR-USD, only US macroeconomic news releases cause severe spikes in the intraday volatility pattern, which are observed for the five-minute intervals ending at 8:35 and 10:05

[23] During winter time conventions the announcement times of 8:30 and 10:00 EST correspond to 13:30 and 15:00 GMT, whereas during DST they correspond to 12:30 and 14:00 GMT.

EST. There is also a clear difference between the sizes of the spikes occurring during the winter and DST periods, with the DST releases causing much larger spikes. Whilst recognising that there are more DST days in the sample than winter time days, this difference can be explained by the downturn in the US economy witnessed during the summer of 2002, as evidenced by worse than expected figures released for many closely watched economic indicators such as Chicago PMI, Consumer Confidence, GDP, University of Michigan Consumer Sentiment Index, Non-Farm Payrolls, Initial Claims for unemployment benefit, the Unemployment Rate and the Philadelphia Federal Reserve Index.

Regularly scheduled US macroeconomic news releases also produce substantial spikes in the intraday volatility pattern for EUR-GBP although of a lower magnitude than for EUR-USD. Spikes occurring outside the US trading session are timed at 8:35 and 11:05 GMT, both of which only occur during DST. The vast majority of UK macroeconomic statistics are publicised at 9:30 London time including information concerning GDP, Industrial Production, Unemployment, Producer Price Index, Consumer Price Index, Retail Sales, the Money Supply and Balance of Trade, explaining the timing of this spike. Although not as extreme as in the US, the poor data released towards the end of the summer in 2002 also reflected a slowdown in the UK economy and the timing of this relatively poor economic performance explains why this spike is more pronounced at 8:35 than 9:35 GMT. Another macroeconomic release of importance to EUR-GBP volatility is the interest rate decision of the Monetary Policy Committee (MPC) of the Bank of England that occurs at mid-day in London on the first Thursday of every month. The spike in EUR-GBP volatility at 11:05 GMT during DST is most likely explained by the announcement by the MPC on 10th July 2003 of a cut in base rates from 3.75% to 3.5%.

For EUR-JPY, volatility spikes are again much more muted than for EUR-USD and the largest spikes occur immediately following US news at 8:00 and 10:00 EST. A relatively small spike at 8:05 GMT during summer time relates to important data releases at 9:00 in London and 10:00 in Europe. In particular, this is the exact timing of announcements of the Purchasing Managers Index, Composite Index, Services Index and Current Account Balance for the Eurozone and the IFO Current Business Conditions and Business Expectations Indices in Germany during summer periods. Noticeably absent for the EUR-JPY intraday volatility pattern are spikes that corresponds exactly to regularly scheduled macroeconomic news announcements in Japan, which take place at 4:30, 5:00, 23:00, 23:30 and 23:50 GMT.

Volatility spikes become even more apparent when intraday patterns are separated by weekdays, identifying the impact of news releases that are announced systematically on the same weekday. The small spike at 00:00 GMT is caused by the opening of markets in Tokyo and may also be influenced by macroeconomic releases from Japan occurring at 23:50 GMT. The remaining peaks on Mondays occur at 8:05, 14:15 and 15:20 GMT, all of which follow the general release times of 8:00, 14:00 and 15:00 GMT very closely, but cannot be attributed to the announcement of a specific economic indicator. The plot for EUR-USD on Tuesdays reveals more interesting results with distinctive spikes at 8:00 and 12:30 GMT corresponding to the release of many different indicators in Europe and the US. The largest spikes in the pattern, showing dramatic five-minute absolute returns of 0.061%, occur during the interval immediately following 10.00 EST when the Consumer Confidence Index is announced by The Conference Board on the last Tuesday of every month.[24] The surge in volatility immediately following these Consumer Confidence numbers demonstrates both the importance that traders in Europe and the US place on consumption expectations when predicting US macroeconomic performance and the dramatic influence that a rigidly scheduled announcement has for information dissemination which impacts on volatility. The timing of this announcement is also important. Released on the final Tuesday of the month, the Consumer Confidence Index offers a measure of consumer expectations based on information gathered during that month. Chronologically, this is one of the first indicators of economic performance that traders observe in a given month, which, in addition to its informational content, may help to explain why the response to its announcement is so volatile.

There are no discernible spikes in EUR-USD volatility for Wednesday, yet the twenty-four hour intraday volatility pattern is clearly evident, whilst Thursdays contain another regularly scheduled release. Initial Claims of unemployment benefit are another closely monitored indicator of US economic performance and are released weekly on Thursday mornings at 8:30 EST by the Department of Labor.

[24] Although not shown, when separating the sample into DST and winter time, the spike at 14:05 GMT measures 0.082% and is larger than the spike of 0.073% at 15:05 GMT confirming the larger spikes found during DST in Figure 3.3.2.2 and attributable to worse than expected data during this period.

Disappointing labour market data in the summer of 2002 ensures a large spike of 0.064% at 12:35 GMT.[25] The Philadelphia Federal Reserve Index is a regional business outlook survey that is published on Thursdays, but at the later time of 12:00 EST. This explains the minor spikes observed at 16:05 GMT and at 17:10 GMT. The EUR-USD volatility spike at 8:30 EST on Fridays is dramatic (and, when averaged over Fridays separated by winter time and DST, are the highest of the entire sample) because they follow the release of one of the most highly scrutinised of all macroeconomic data releases, the Employment Report. Announced on the first Friday of every month by the Bureau of Labor Statistics of the US Department of Labor, the Employment Report comprises the change in Non-Farm Payrolls, the Unemployment Rate, the length of the average workweek and hourly earnings. In addition to the information regarding labour market conditions contained in this announcement, the Employment Report is an important indicator because, along with the Consumer Confidence Index, it is another early indicator of economic performance in a particular month. Released on the first Friday of every month, the data relate to US labour market conditions for the previous month. Subsequent news announcements relating to the same month will not come as such of a surprise to traders given what they have already learned from the Consumer Confidence Index and Employment Report. The University of Michigan Consumer Sentiment Index is also released on Fridays, but not until the later time of 10:00 EST. This explains the volatility spikes at 14:05 GMT in DST and 15:05 GMT in winter time.

The results for EUR-GBP volatility in Figure 3.3.5.2 are far less dramatic and, somewhat surprisingly, there are no extreme spikes in EUR-GBP volatility corresponding to European or UK macroeconomic announcements, implying that macroeconomic indicators for these regions do not, on average, produce large price reactions when they are announced. As with EUR-USD, the US Consumer Confidence Index and the Employment Report generate spikes in EUR-GBP volatility on Tuesdays and Fridays, respectively. Although the impact on volatility of news relating to the performance of the US economy is much smaller for EUR-GBP than EUR-USD, it is surprising that US news creates more prominent and frequent spikes than European and UK news. This may be explained by a triangulation arbitrage relationship where the EUR-GBP exchange rate adjusts to ensure that no

[25] Again, separation of the sample between DST and winter time reveals a larger spike for the DST period (0.095% compared to 0.075%).

arbitrage opportunities exist between EUR-USD, EUR-GBP and GBP-USD. These price adjustments manifest themselves as increased volatility for EUR-GBP. If traders in the US pay most attention to their domestic currency (USD), the release of US macroeconomic data causes a surge in volatility for exchange rates paired against the dollar, EUR-USD and GBP-USD in this case. To ensure the absence of arbitrage opportunities, the EUR-GBP exchange rate would adjust quickly to reflect the different dollar price of both EUR and GBP.

There are only two spikes in EUR-GBP volatility that distinguish themselves from the underlying intraday U-shape during the European trading session, and even these are small in comparison to the peaks found for EUR-USD volatility during the US trading session. First, macroeconomic news announced at 8:00 GMT on Mondays contributes to an average five-minute absolute return of 0.038%, and such announcements include the Eurozone's Purchasing Managers Index, Composite Index and Services Index and German IFO Current Business Conditions and Business Expectations Surveys, but neither indicator was released consistently on Mondays throughout the sample. Second, the spike at 11:05 GMT on Thursdays (five-minute absolute return of 0.035%) follows the Bank of England's Monetary Policy Committee's decisions on UK base rates.

Figure 3.3.5.3 shows similar patterns for EUR-JPY volatility. US macroeconomic news announcements again cause spikes on Tuesdays, Thursdays and Fridays in response to the release of the US Consumer Confidence Index, Initial Claims and the Employment Report with the increased volatility of EUR-JPY explained by the adjustment of the exchange rate to ensure the absence of arbitrage opportunities in the triangular relationship between EUR-USD, USD-JPY and EUR-JPY. Although EUR-JPY volatility is higher during the Asian trading session compared to the other two exchange rates, the only clear spikes during this trading session occur at 1:00 GMT on Mondays and Fridays, 2:30 and 3:45 GMT on Mondays, which are difficult to reconcile with the release of Japanese macroeconomic information.[26] Of the European macroeconomic announcements, the release of the French Services Index may explain the spike in EUR-JPY volatility on Tuesdays at 8:50 GMT, but this indicator is released on only two Tuesdays during the sample. Announcements timed at 6:00 GMT on Fridays include the Trade

[26] The spike in EUR-JPY at 3:45 GMT is speculated to be caused by the intervention of the Bank of Japan supporting the dollar on Monday 24th June 2002.

Balance, Current Account Balance, IFO Manufacturing Survey, Producer Prices, Import Prices and Retail Sales for Germany, explaining the spike at 6:05 GMT.

Figure 3.3.6.1 seeks further evidence on the distortion of the intraday volatility pattern by spikes caused by macroeconomic news announcements. Concentrating on EUR-USD only, since the spikes for EUR-GBP and EUR-JPY in Figures 3.3.5.2 to 3.3.5.3 are small by comparison, intraday volatility patterns are plotted for days on which US announcements were made in the left hand graphs and on days when no US announcements were made on the right hand side. Average volatility in the first row is based on 313 announcement days and 99 non-announcement days. The number of days included for winter time, shown in the second row, is 133 announcement days and 40 non-announcement days, whilst patterns for DST days shown in the third row are based on 180 announcement days and 59 non-announcement days. Two important findings emerge from the plots. First, volatility spikes only occur on days which include an announcement of US news confirming that these are the cause. Spikes are larger during the summer time owing to the US economic downturn experienced in the summer of 2002 and the larger sample of summer time days may also be a contributing factor. Second, the twenty-four hour intraday volatility pattern is robust to non-announcement days and the underlying pattern is identical in magnitude on announcement and non-announcement days, showing that the peaks of U-shapes are not caused by the release of US macroeconomic news, rather the patterns are a stylised feature of asset returns. The pattern is shifted leftwards by one precisely one hour during DST confirming the findings of section 3.3.4. Superimposing the patterns for announcement days onto that for non-announcement days reveals that the patterns are almost identical, apart from the elevated volatility around the news release times.

In a further attempt to demonstrate the impact of macroeconomic news on exchange rate volatility, Tables 3.3.6.1 to 3.3.6.3 display the fifteen largest absolute five-minute returns for each exchange rate with possible explanations for the causes of the abrupt price changes. Although a subjective analysis, the evidence in Table 3.3.6.1 is striking. Eleven of the fifteen events occur immediately after the release of macroeconomic news, with the Employment Report featuring very prominently.

Figure 3.3.6.1. EUR-USD Intraday Volatility on US Announcement Days.

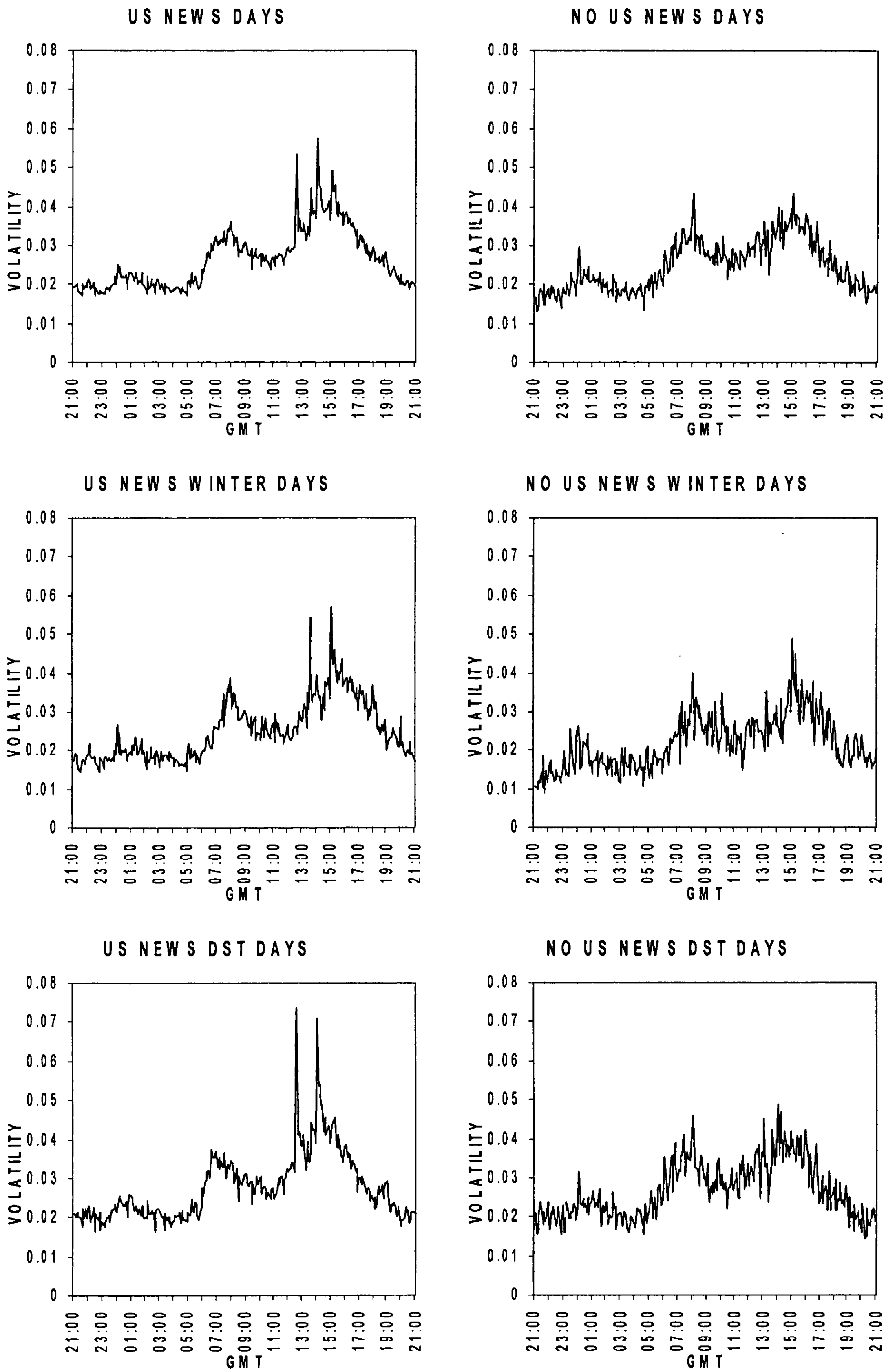


Table 3.3.6.1. Largest Five-Minute Absolute Returns for EUR-USD.

VOLATILITY	DATE	GMT	WEEKDAY	EXPLANATION
0.525	07.02.2003	13:35	Friday	Employment Report
0.456	10.01.2003	13:35	Friday	Employment Report
0.433	31.07.2003	12:35	Thursday	GDP Advance Initial Claims
0.414	06.09.2002	12:35	Friday	Employment Report
0.404	27.08.2002	14:05	Tuesday	Consumer Confidence
0.397	13.03.2003	18:55	Thursday	
0.380	19.06.2003	16:05	Thursday	Philadelphia Fed. Index
0.378	28.06.2002	14:05	Friday	Chicago PMI Michigan Sentiment Index
0.372	28.10.2002	15:20	Monday	
0.366	17.03.2003	16:10	Monday	
0.357	05.06.2003	12:05	Thursday	50 bp cut in ECB Refinancing Rate
0.355	06.11.2002	19:25	Wednesday	50 bp cut in Fed Funds Rate
0.354	03.06.2002	14:15	Monday	ISM (Manufacturing) Index
0.344	27.06.2002	15:15	Thursday	
0.344	03.10.2002	14:05	Thursday	ISM (Non-Manufacturing) Index

Table 3.3.6.2. Largest Five-Minute Absolute Returns for EUR-GBP.

VOLATILITY	DATE	GMT	WEEKDAY	EXPLANATION
0.922	09.06.2003	08:05	Monday	Early European trading on Monday
0.904	01.04.2002	22:20	Tuesday	Early Sydney trading after holiday
0.634	20.07.2003	21:10	Monday	Early Sydney trading on Monday
0.598	20.07.2003	21:25	Monday	Early Sydney trading on Monday
0.555	23.12.2002	07:10	Monday	Early European trading on Monday
0.548	10.07.2003	11:05	Thursday	BoE reduces rates by 25bp to 3.5%
0.548	23.12.2002	07:15	Monday	Early European trading on Monday
0.488	20.01.2003	21:55	Monday	Early Sydney trading on Monday
0.398	22.01.2003	06:00	Wednesday	Early European trading
0.384	22.01.2003	03:45	Wednesday	
0.383	22.01.2003	06:05	Wednesday	Early European trading
0.374	09.06.2003	08:10	Monday	Early European trading on Monday
0.353	22.01.2003	03:20	Wednesday	
0.342	15.12.2002	22:25	Monday	Early Sydney trading on Monday
0.335	01.04.2002	22:30	Tuesday	Early Sydney trading after holiday

Table 3.3.6.3. Largest Five-Minute Absolute Returns for EUR-JPY.

VOLATILITY	DATE	GMT	WEEKDAY	EXPLANATION
1.031	24.06.2002	03:45	Monday	Bank of Japan intervention
0.663	28.06.2002	14:05	Friday	Chicago PMI Michigan Sentiment Index
0.576	22.05.2002	05:40	Wednesday	Early European trading
0.555	26.06.2002	05:00	Wednesday	Early European trading
0.539	06.12.2002	14:25	Friday	
0.510	07.03.2002	16:10	Thursday	
0.485	04.06.2002	12:35	Tuesday	
0.478	26.09.2002	14:05	Thursday	US New Home Sales
0.464	18.04.2002	16:20	Thursday	Philadelphia Fed. Index
0.457	31.05.2002	06:00	Friday	German IFO Manufacturing Survey
0.452	07.03.2002	15:05	Thursday	
0.452	23.05.2002	09:20	Thursday	
0.448	03.03.2003	18:25	Monday	
0.416	05.06.2002	21:40	Wednesday	Early Sydney trading
0.405	06.06.2003	12:45	Friday	Employment Report

Other important announcements include the GDP Advance, Initial Claims, Consumer Confidence, Philadelphia Federal Reserve Index, Chicago Purchasing Managers Index (PMI), University of Michigan Consumer Sentiment Index, Federal Open Market Committee (FOMC) interest rate decisions and Institute of Supply Management (ISM) Index. Given the larger volatility spikes witnessed during the economic slowdown in the US during the summer of 2002 shown in Figures 3.3.4.1 and 3.3.5.1, it would not be surprising to find the intervals of largest absolute returns to occur during this period. The evidence in Table 3.3.6.1, however, suggests that this is not the case with only four of the eleven intervals falling in the summer of 2002. This demonstrates that the spikes found in the intraday EUR-USD volatility pattern, as shown in Figures 3.3.4.1 and 3.3.5.1, are not caused by a small number of extremely large price adjustments in response to particularly bad news. Rather, it demonstrates the importance of macroeconomic announcement effects as a component of volatility driving short lived episodes of extreme volatility.

To explain the remaining four absolute five-minute returns for EUR-USD, we can speculate that some were caused by events surrounding war in Iraq. In the order that the intervals appear in Table 3.3.6.1, on Thursday 13th March 2003 the US announced that it would wait only one more week for a UN vote on Iraq's final ultimatum and, even then, may not ask for a vote at all implying the imminence of military action in Iraq. White House spokesman Ari Fleischer declared "the end is coming into sight." In the previous Autumn, France announced on 28th October 2002 that it would not support any clause in a UN resolution that could give the US automatic authority to take military action if Iraq was deemed to be in breach of the new weapons inspections regime, heightening tension between allied forces. On 17th March 2003, US President George Bush ordered Saddam Hussein and his sons to leave Iraq within 48 hours, giving a precise time frame for his intention to begin military action. Without knowing the exact timing of these three events it is impossible to confirm that they are the single cause of the high EUR-USD volatility. However, it is not surprising that exchange rates witnessed high volatility on the days of these dramatic events, especially during a period of extreme global tension. The large absolute return at 15:15 GMT on 27th June 2002 is as yet unexplained.

Table 3.3.6.2 shows the same analysis performed on the EUR-GBP exchange rate but with less dramatic results. Even though there are some intervals with larger absolute returns for EUR-GBP than EUR-USD, the lack of macroeconomic news announcements as possible explanations for high absolute returns shows that EUR-GBP is less responsive to macroeconomic news than EUR-USD, even for UK and Eurozone announcements. This is confirmed by the absence of extreme volatility spikes in the graphs of intraday volatility shown in Figures 3.3.4.1 and 3.3.5.2. As previously noted, the most important single macroeconomic news announcement for EUR-GBP during the sample was made by the Bank of England on Thursday 10th July 2003 when the Monetary Policy Committee reduced UK base rates by 25 basis points from 3.75% to 3.5%. Of the remaining 14 high volatility intervals, six can be explained by traders in Sydney and Wellington adjusting prices to reflect information made available over weekends. A further six intervals exhibit high volatility during early trading in Europe and the UK. This leaves two five-minute intervals that witness a high absolute EUR-GBP return with no obvious macroeconomic announcement or calendar effect as an explanation. It is revealing, however, that these two intervals, along with other intervals during early trades in Sydney and Europe occur in pairs where the intervals are very close to each other. This suggests that traders make dramatic changes to their quotes, especially to reflect weekend events, only to amend those quotes back towards their original levels slightly later. This activity manifests itself in Table 3.3.6.2 as two very close intervals in the same day showing high absolute returns.

Finally, for EUR-JPY, the largest absolute five-minute return in Table 3.3.6.3 occurs during the Asian trading session and is speculated to be the result of intervention by the Bank of Japan to support USD against JPY. Five of the remaining fourteen large absolute five-minute returns occur immediately after the release of macroeconomic news. Four of these intervals relate to US news including Chicago PMI, Michigan Sentiment Index, New Home Sales, Philadelphia Federal Reserve Index and the Employment Report with three of the four falling during the US economic slowdown of the summer of 2002. The simultaneous release of Chicago PMI and the University of Michigan Sentiment Index at 10.00 EST on 28th June 2002 caused the second largest absolute return in any one five-minute interval for EUR-JPY and also the 12th largest five-minute absolute return for EUR-USD, and this is the only announcement that appears in Tables 3.3.6.1 to 3.3.6.3 for two different exchange rates. This evidence confirms the influence of US macroeconomic news on EUR-JPY volatility, which is greater than its effect on EUR-GBP, and again shows the possible triangular arbitrage relationship between EUR-JPY, EUR-USD and USD-JPY. There is also a large absolute return for EUR-JPY in an interval corresponding to the release of the German IFO Manufacturing Survey representing the only European macroeconomic announcement to cause any of the fifteen largest absolute five-minute returns for each of the three EUR exchange rates. Of the remaining nine large absolute five-minute returns for EUR-JPY, one occurs during early trading in Sydney and two are during early European trading showing that volatility increases at the opening of trading in financial centres as previously identified from the intraday volatility plots. The other six intervals occur during European or US trading sessions when volatility tends to be higher during the trading hours of the most active financial centres. Perhaps a little surprising is the absence in Table 3.3.6.3 of any Japanese macroeconomic announcements or market openings in Tokyo, Hong Kong, Singapore and Malaysia as causes of the large absolute five-minute returns for EUR-JPY.

3.3.7 Macroeconomic News Announcement Window

The final stage of this preliminary analysis of macroeconomic announcement effects investigates the short run behaviour of EUR volatility in the two hours immediately preceding and following an announcement. Absolute five-minute returns during each interval for this four hour window that includes a macroeconomic announcement are averaged within intervals and across announcements for each of the three currencies. These average patterns are plotted in Figures 3.3.7.1 to 3.3.7.8 where EUR-USD, EUR-GBP and EUR-JPY are shown as red, blue and green lines, respectively, and the announcement is made at minute zero. The sample contains announcements of 132 separate macroeconomic indicators over a 19 month period.[27] To ensure that averages are calculated over a reasonable number of observations and to conserve space, news announcements are grouped into separate categories rather than being analysed individually. Figure 3.3.7.1 shows the average volatility pattern for macroeconomic news separated by country. Figure 3.3.7.2 groups news from all countries together, but separates news into general macroeconomic categories such as real output, consumption, investment, government finances, balance of payments, inflation, forward looking, interest rate and monetary news.

[27] Specifically, there are 37 indicators for the US, 21 for the Eurozone, 18 for Germany, 17 for France, 19 for the UK and 20 for Japan.

Figure 3.3.7.1. Average Volatility around News Categorised by Country.

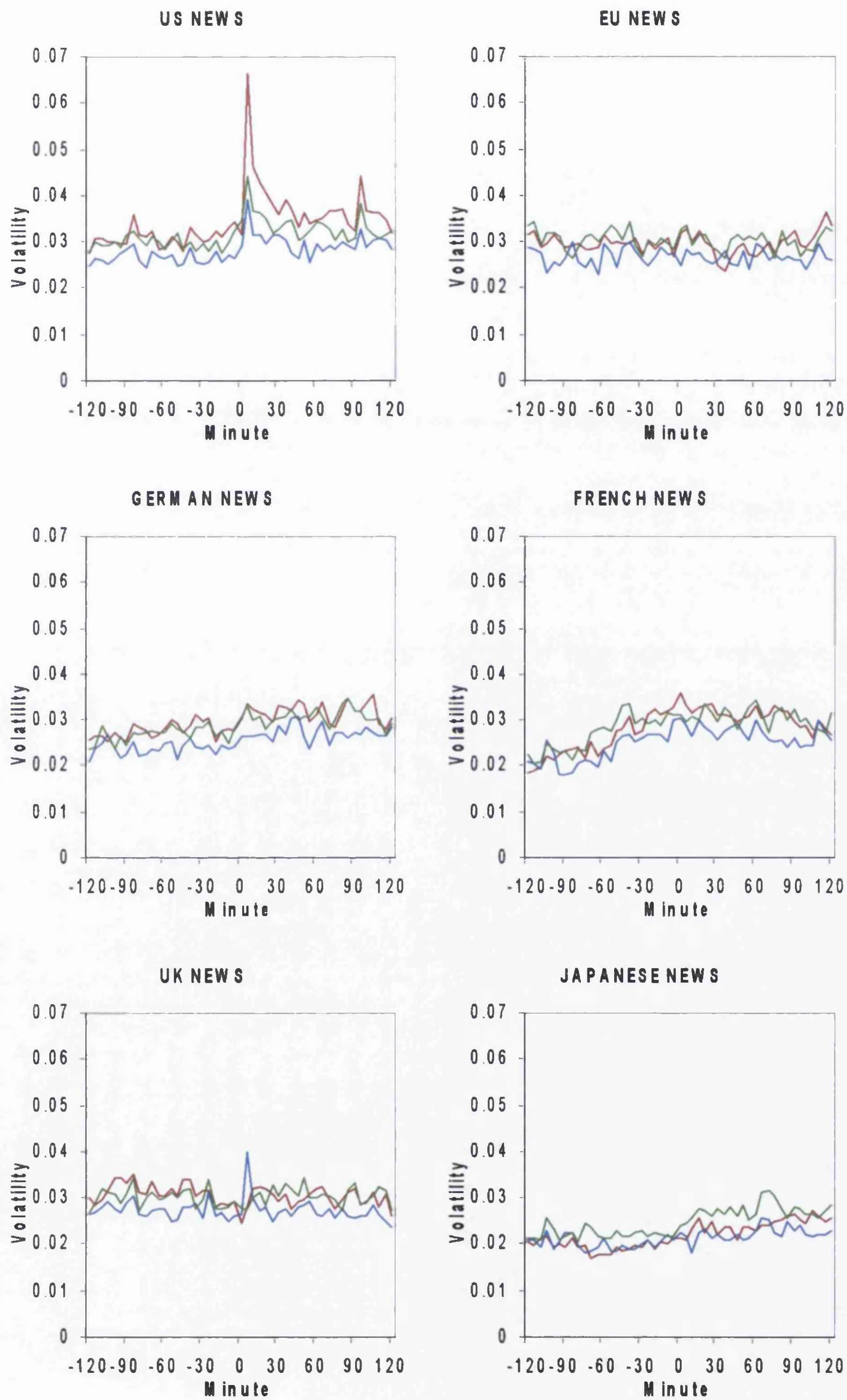


Figure 3.3.7.2. Average Volatility around News Categorised by Announcement Type.

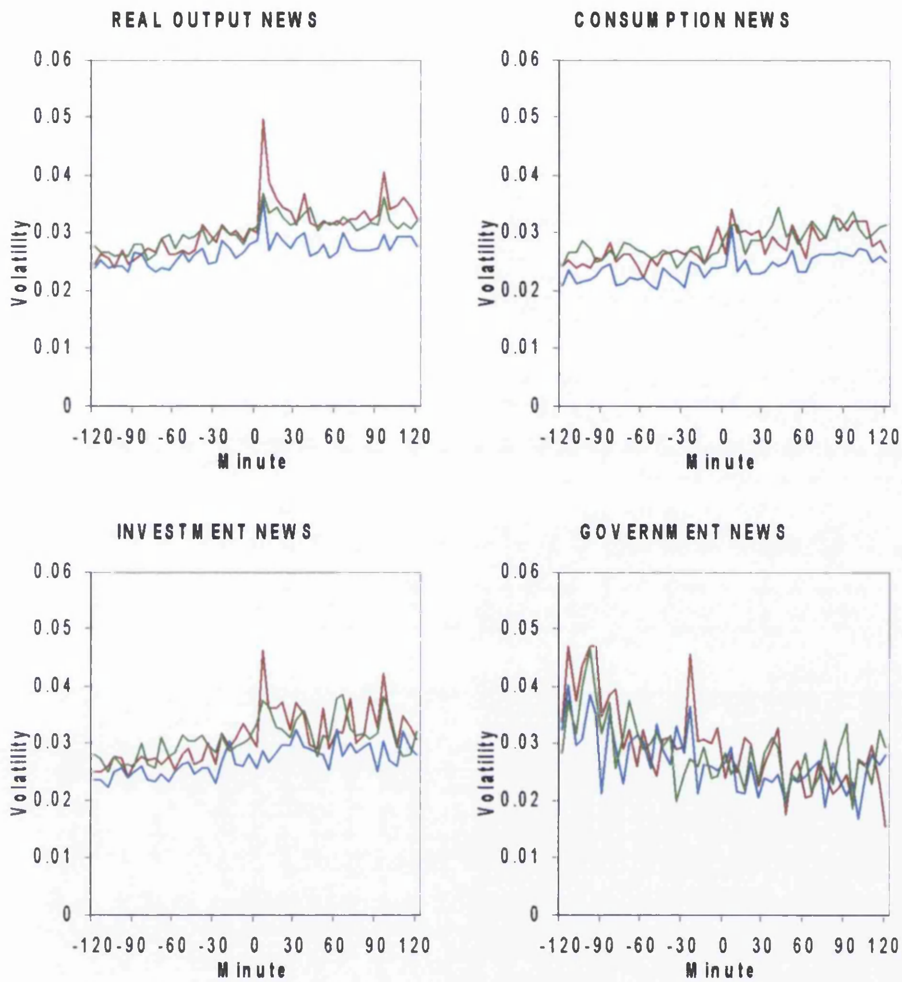


Figure 3.3.7.2. (Continued)

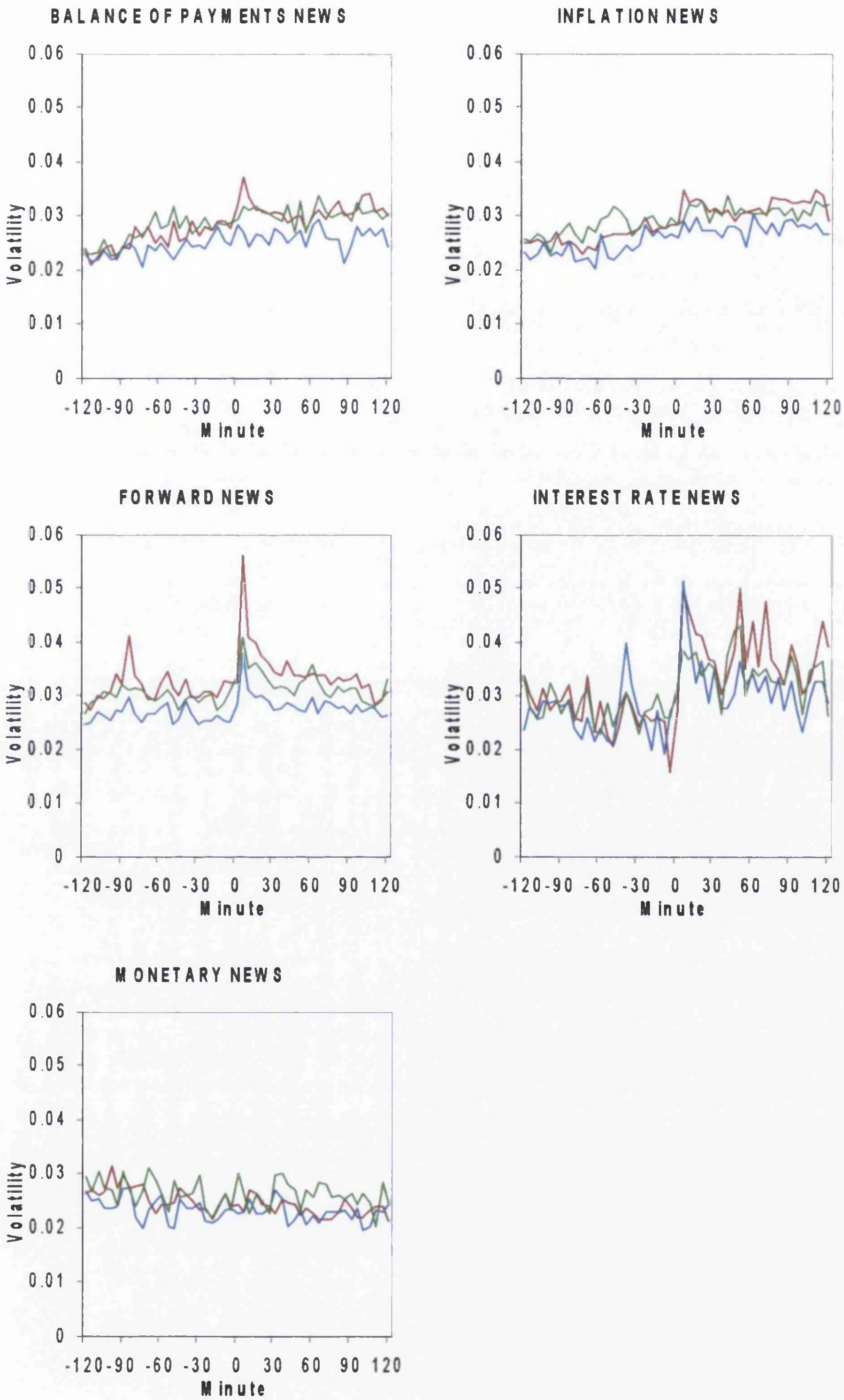


Figure 3.3.7.3. Average Volatility around US News Categorised by Announcement Type.

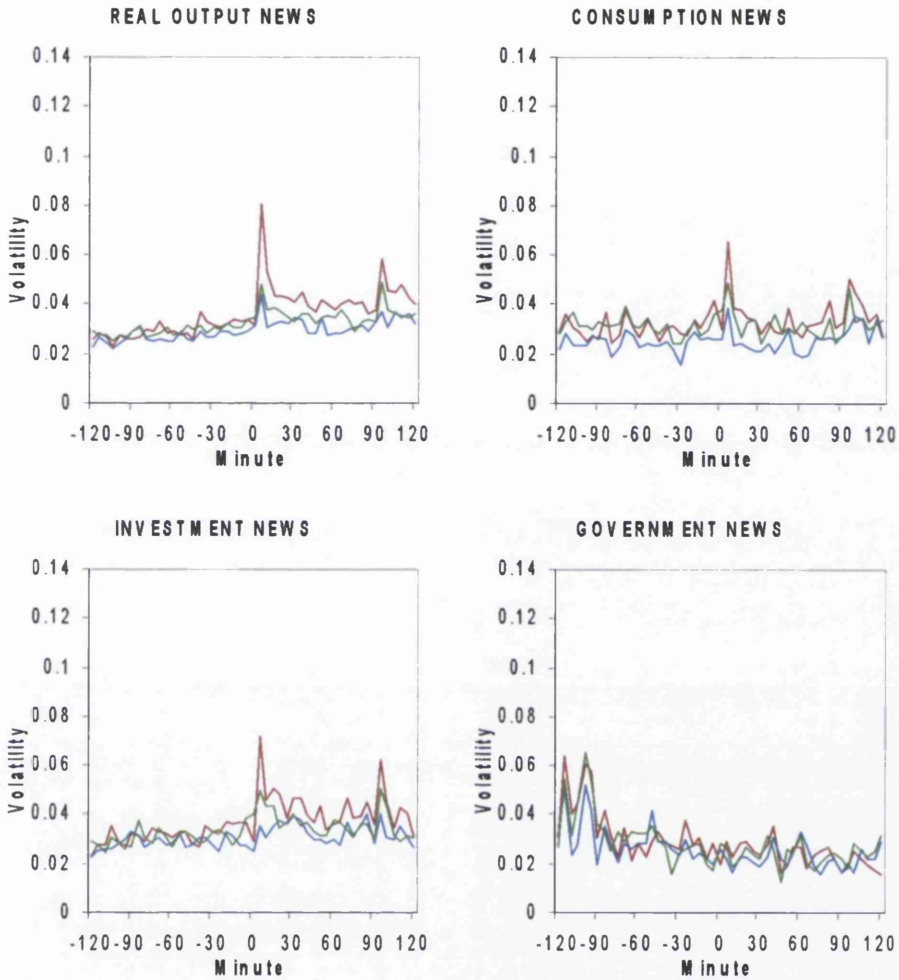


Figure 3.3.7.3. (Continued)

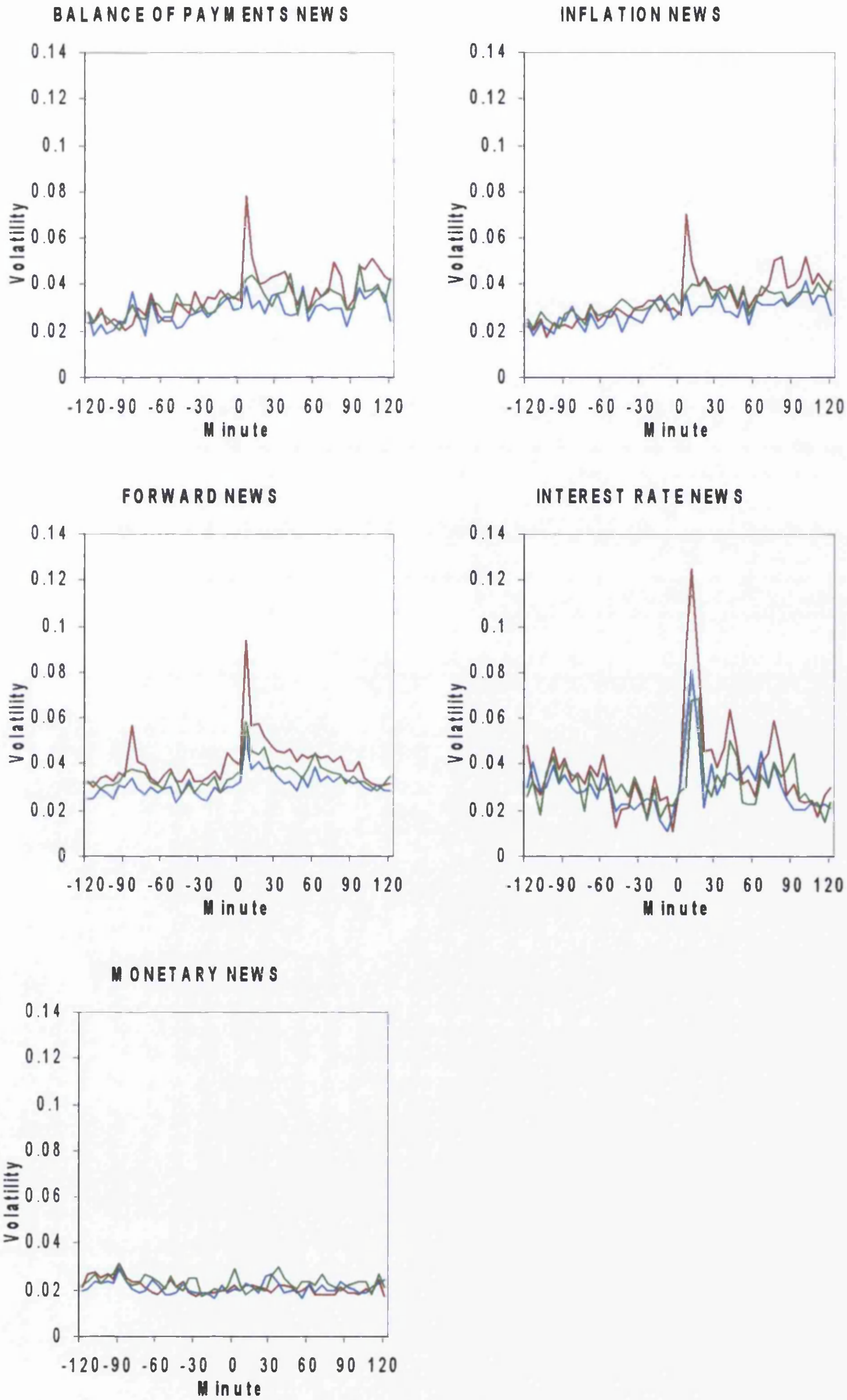


Figure 3.3.7.4. Average Volatility around Eurozone News Categorised by Announcement Type.

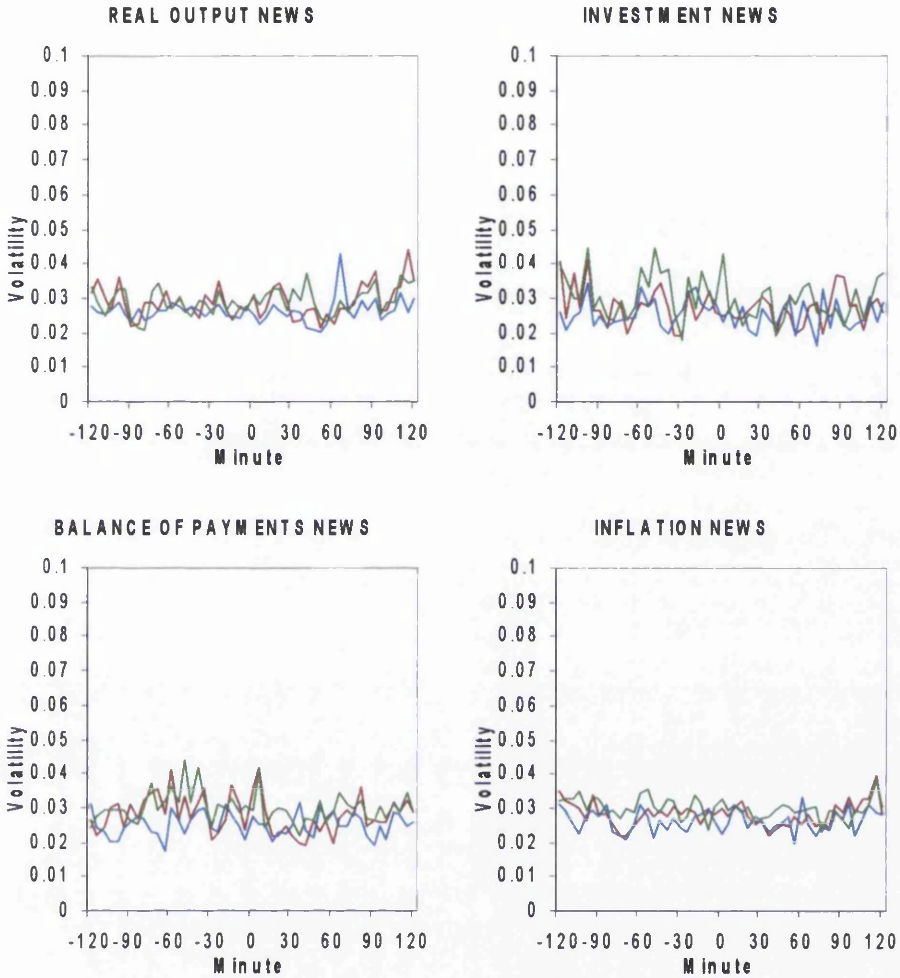
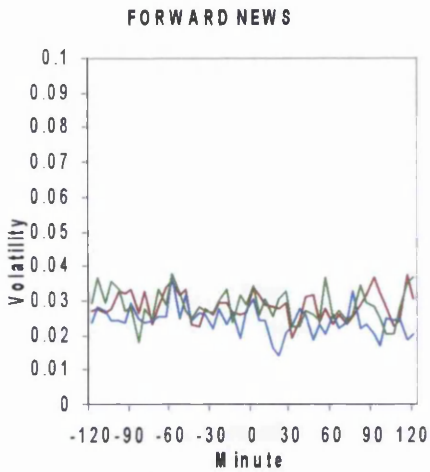
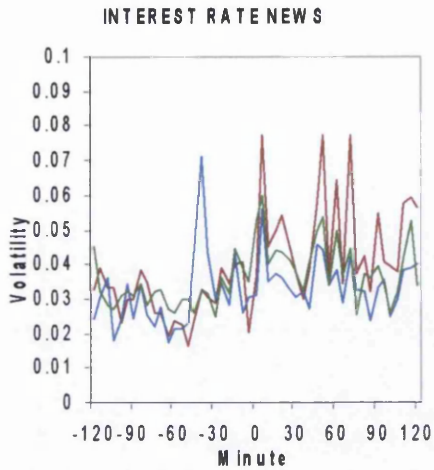


Figure 3.3.7.4. (Continued)





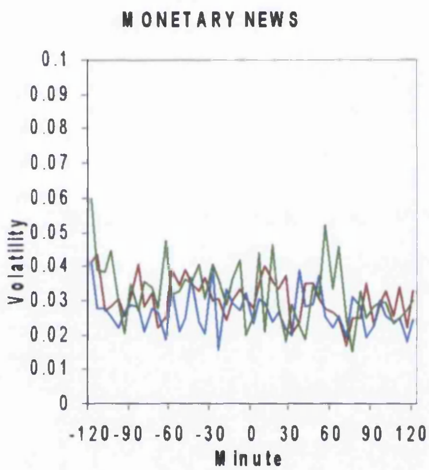


Figure 3.3.7.5. Average Volatility around German News Categorised by Announcement Type.

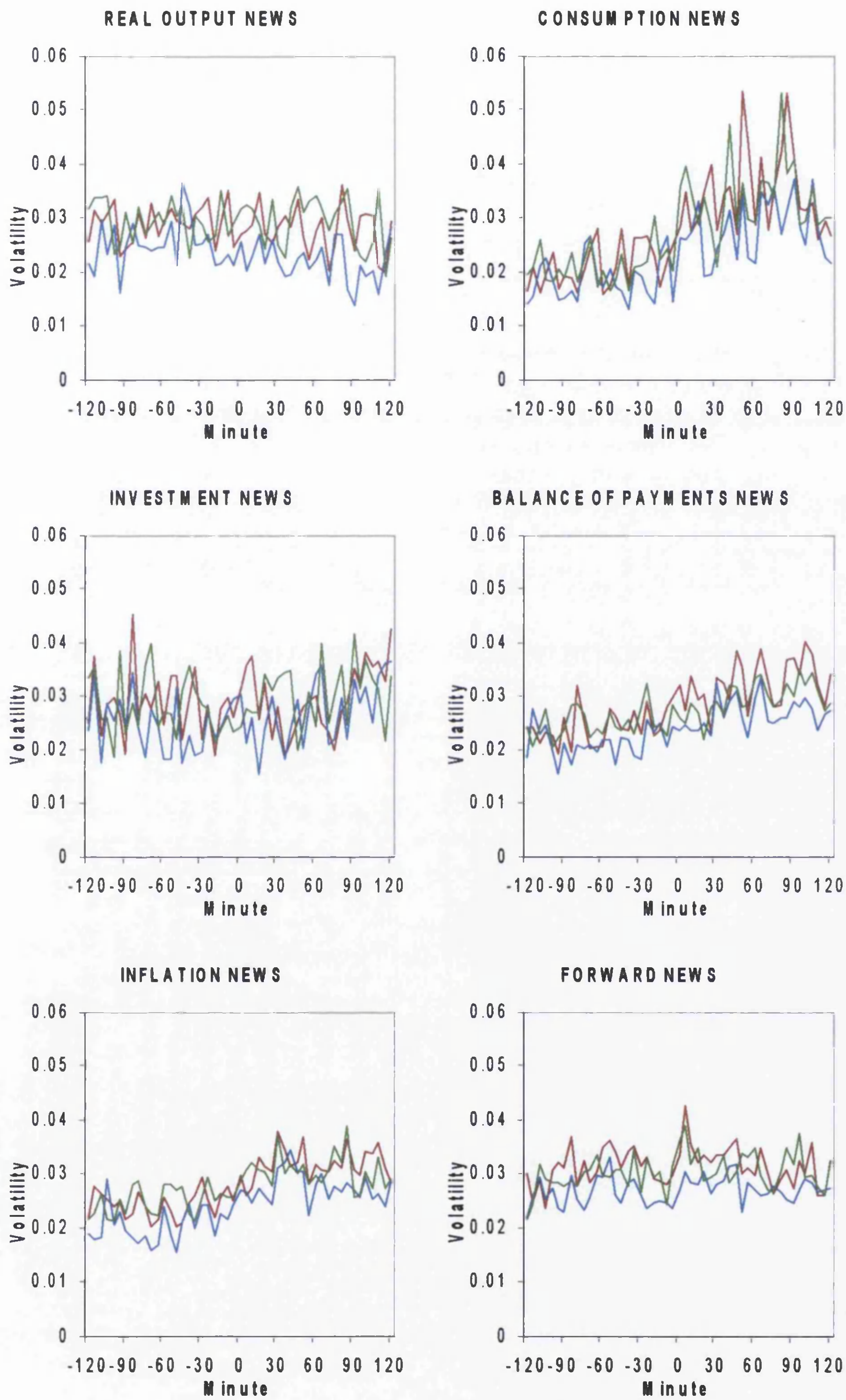


Figure 3.3.7.6. Average Volatility around French News Categorised by Announcement Type.

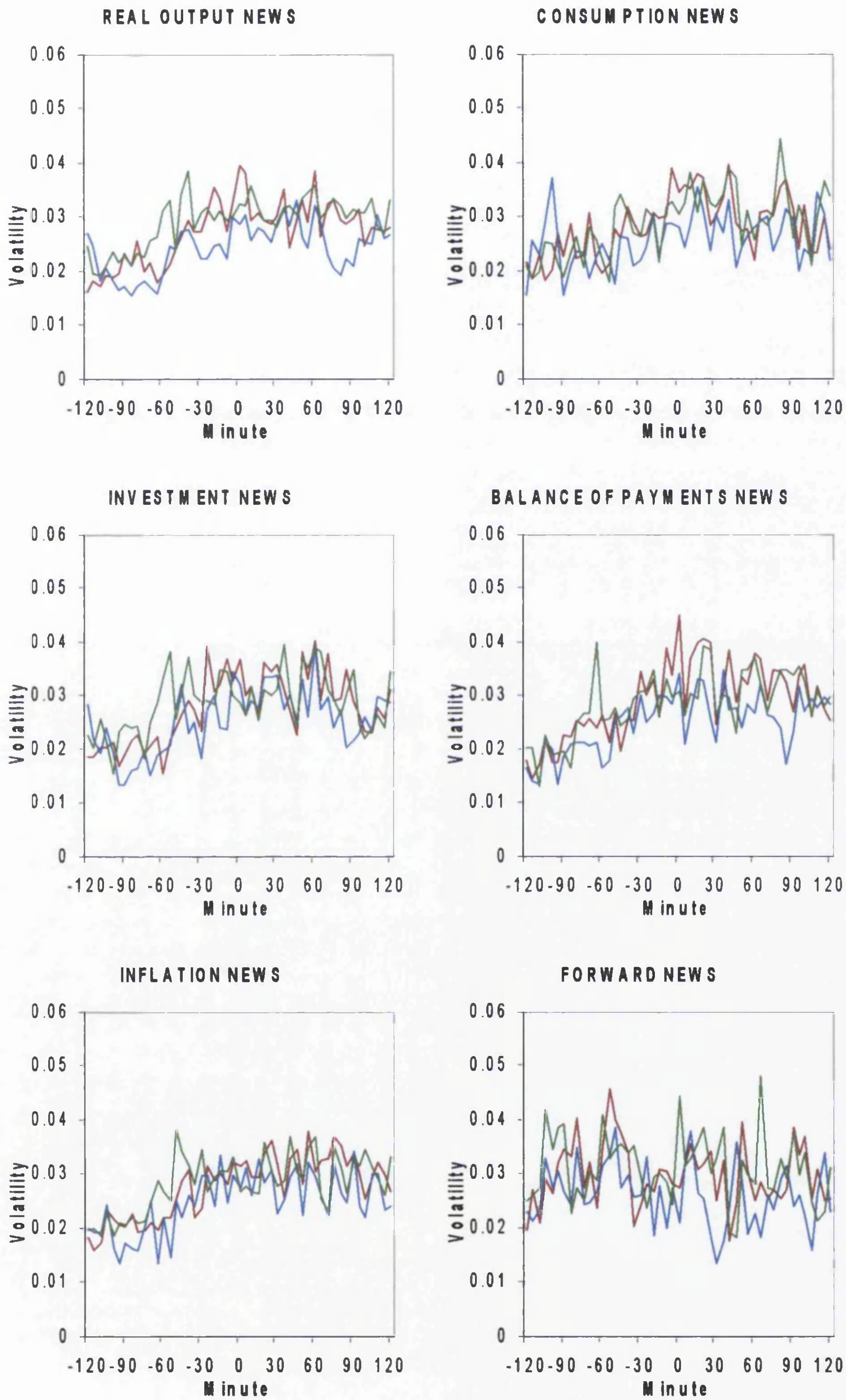


Figure 3.3.7.7. Average Volatility around UK News Categorised by Announcement Type.

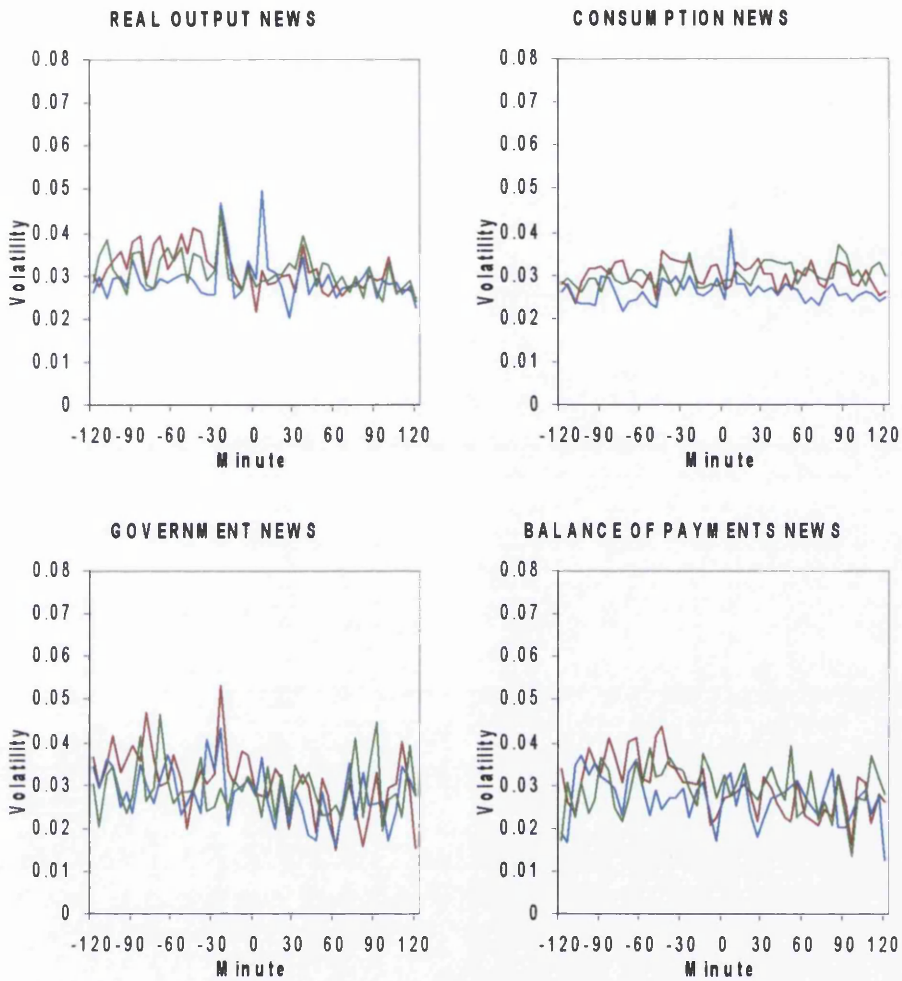


Figure 3.3.7.7. (Continued)

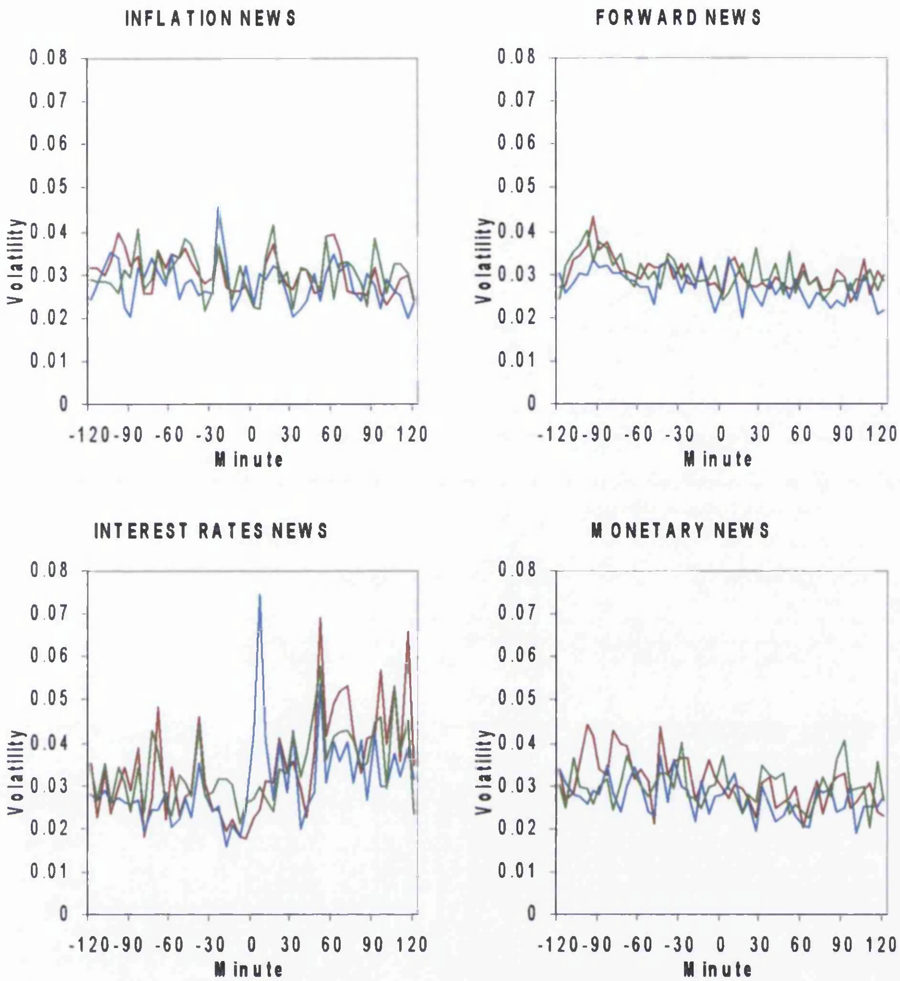


Figure 3.3.7.8. Average Volatility around Japanese News Categorised by Announcement Type.

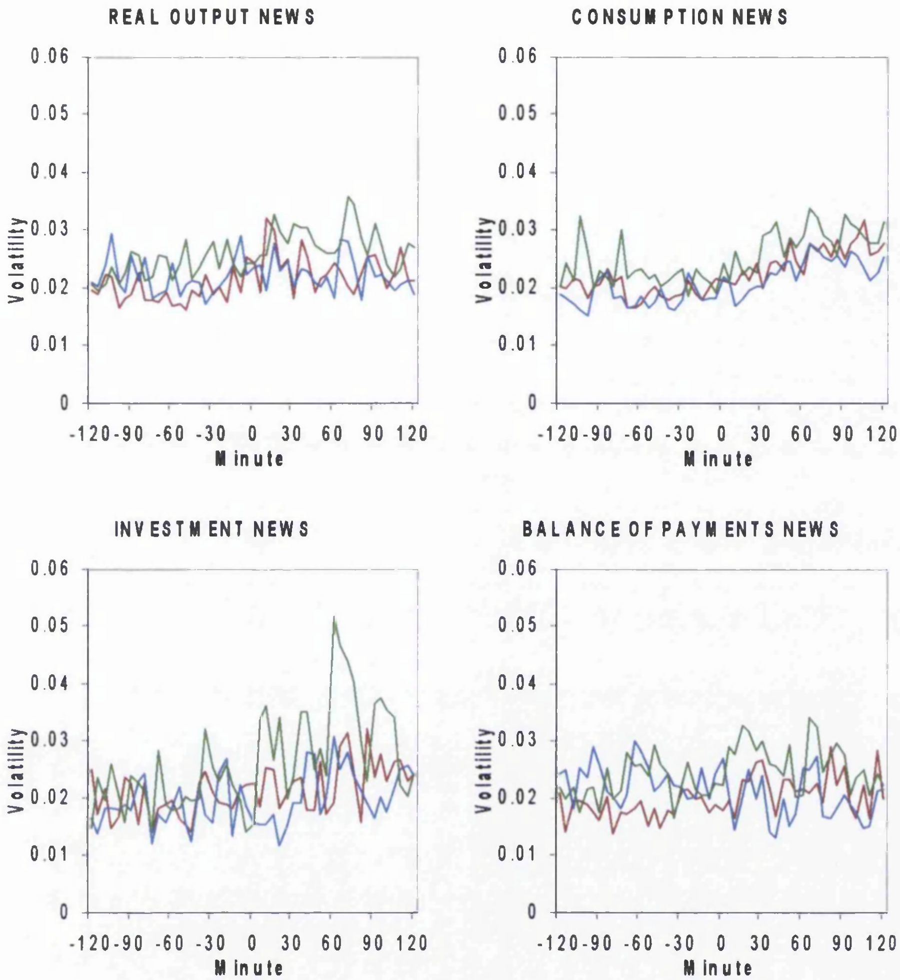
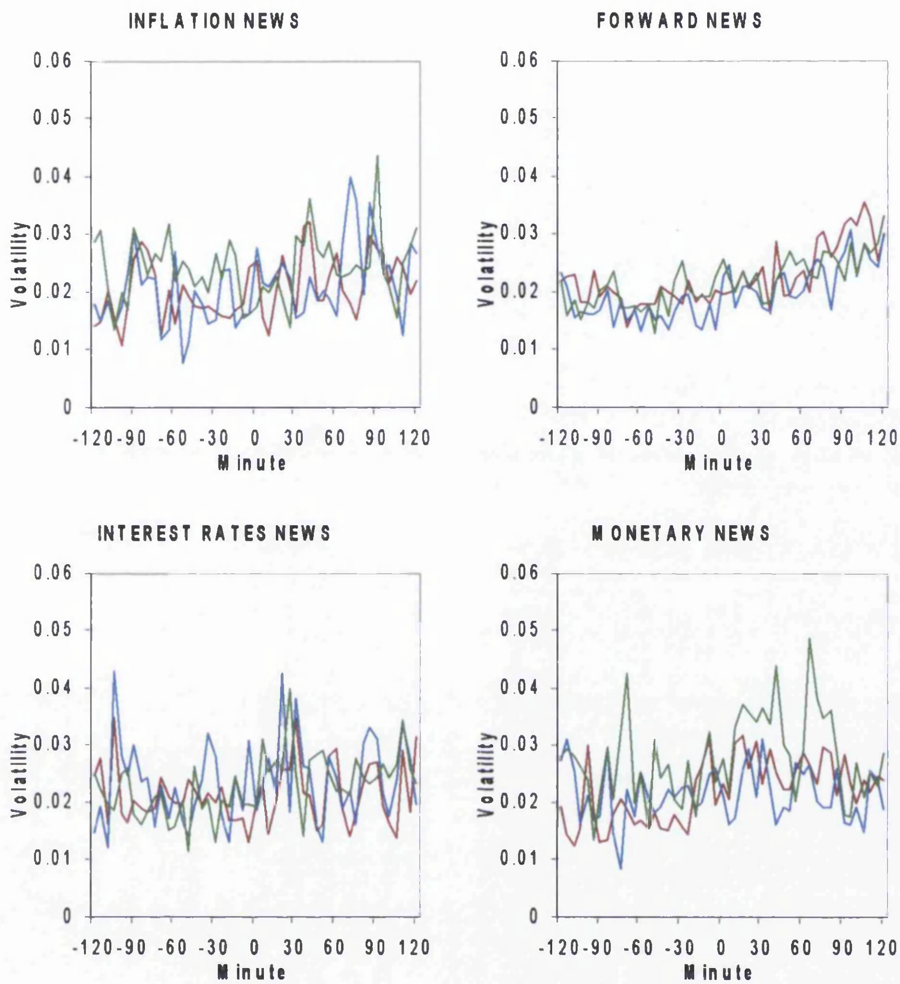


Figure 3.3.7.8. (Continued)



It is possible that the effect of certain announcements may be muted by averaging and so Figures 3.3.7.3 to 3.3.7.8 also plot the very short run volatility pattern around announcements categorised by both country and macroeconomic announcement type.

Figure 3.3.7.1 reveals that the announcement of news relating to the US economy causes a large spike in volatility. The largest spike is seen for EUR-USD, but there are also spikes for EUR-GBP and EUR-JPY. Volatility appears to rise slightly just before the announcement, which may reflect information leakage, anticipatory trading, trader positioning or hedging or simply the rise in volatility in accordance with the underlying intraday volatility pattern. Volatility then remains elevated afterwards, showing a slowly decaying pattern. Volatility also appears to be higher after the announcement then before the announcement. Spikes timed ninety minutes before and after an announcement are also caused by US macroeconomic news releases as US news is regularly released at 8:30 and 10:00 EST, so announcements occurring on the same day and ninety minutes apart cause these secondary spikes. Macroeconomic news from the remaining countries does not appear to cause such a dramatic reaction, apart from the effect of UK news on EUR-GBP volatility.

The largest reactions in volatility in Figure 3.3.7.2 are caused by real output news, including GDP, Industrial Production, Employment and Productivity; forward looking indicators such as Consumer Confidence, Business Confidence, Business Expectations, Purchasing Managers Indices and regional business activity surveys; and interest rate announcements. From the evidence presented in Figure 3.3.7.1, it is likely that announcements of these types relating to the US economy cause the most dramatic reactions in volatility. Figures 3.3.7.3 to 3.3.7.8 confirm this and show that, although averaging over fewer announcement days, reactions to news are more volatile when separating the important US announcements from the less important announcements from other countries. News about US government finances and money supply cause no spike in volatility. Of the other countries, interest rate announcements by the ECB, German forward looking indicators, French real output, balance of payments and forward looking announcements, and UK real output and interest rate decisions, all appear to be important. Although EUR is volatile around the announcement of Japanese news, there is no clear surge in volatility following any of the Japanese releases. It is clear from Figures 3.3.7.1 and 3.3.7.2 that volatility remains elevated for several intervals after the release of macroeconomic news indicating that the initial response persists and decays only slowly. There is also evidence that volatility increases leading up to announcements, which may indicate information leakage, with price fluctuations resulting from trading activity in anticipation of the announcement or simply a rise in volatility in accordance with the underlying intraday volatility pattern.

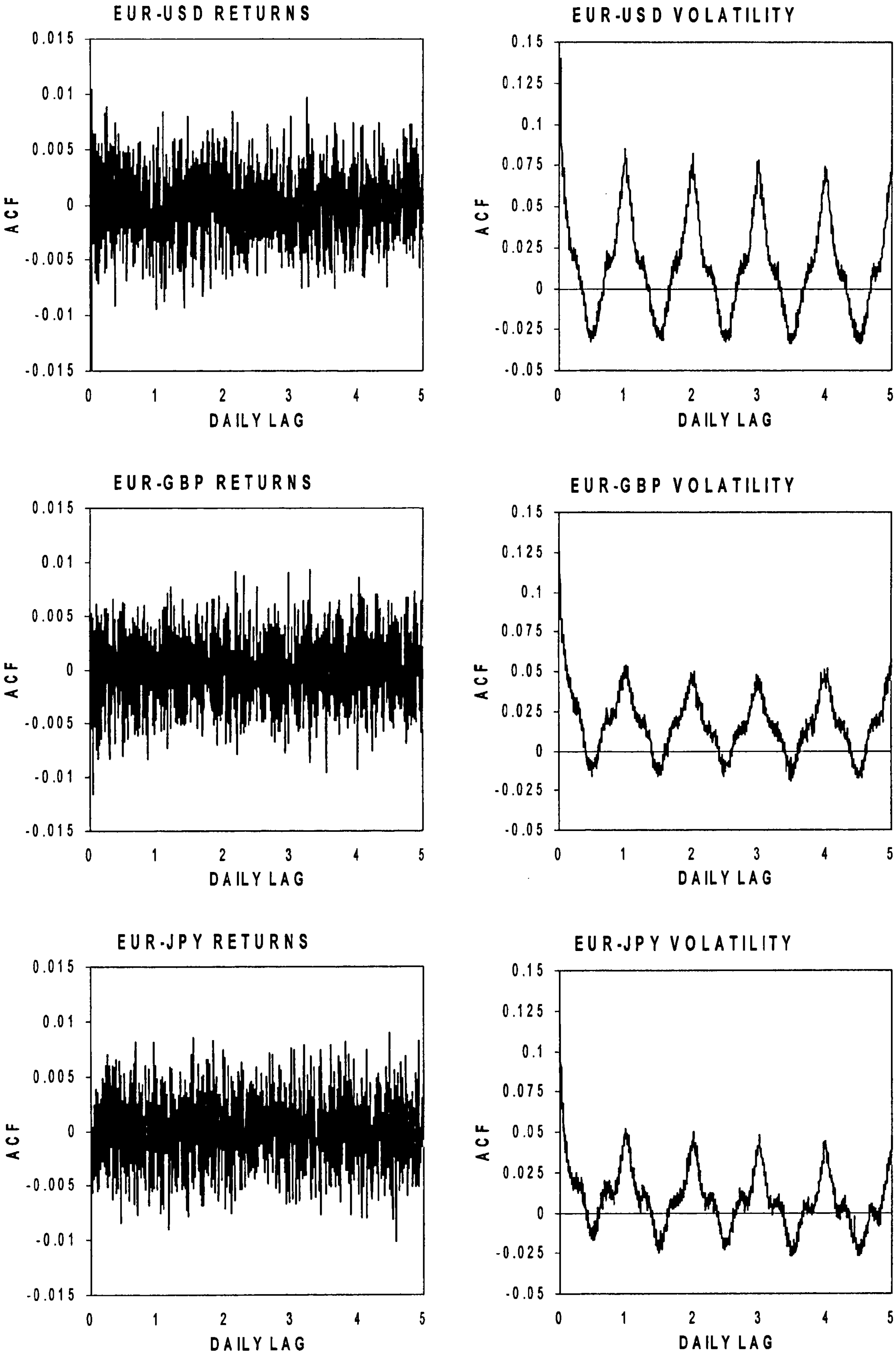
In brief summary, the preliminary analysis so far has revealed two important components of exchange rate volatility. Firstly, calendar effects are shown by pronounced twenty four hour intraday volatility patterns that display higher volatility at times when financial centres begin trading and particularly when trading activity in disparate regions overlaps. This section has also revealed the importance of macroeconomic announcements as a second component of EUR volatility, whereby disruptions to the distinctive intraday volatility patterns, or extreme spikes, occur during intervals immediately following macroeconomic news releases and these also help to explain some of the largest absolute five-minute returns of the sample. Further, when isolating a four-hour window containing macroeconomic news announcements, there is a slight increase in volatility just before the release, a violent jump in volatility immediately following the announcement and a period of elevated volatility afterwards when the effect slowly dissipates. Notably, US news causes the most violent reactions to EUR volatility, with real output, forward looking indicators and interest rate announcements particularly important.

The objective of the remainder of this study is to identify which individual announcements are statistically significant determinants of exchange rate volatility, but the incremental contribution to volatility of news announcements can only be isolated after explicit modelling of the stylised intraday pattern. Extending the understanding of the dynamics of volatility surrounding macroeconomic news announcements is the primary objective of this chapter and so the behaviour of volatility in the intervals immediately before and after announcements also warrants explicit, robust econometric treatment.

3.3.8 Long Memory Time Series Properties

Turning to the time series properties of high frequency exchange rate returns, Figure 3.3.8.1 shows plots of the autocorrelation functions (ACF's) calculated to 1,440 lags, corresponding to exactly five days, for five-minute returns and absolute five-minute returns.

Figure 3.3.8.1. Five-Day Correlograms for Five-Minute Returns and Absolute Returns.



For each currency, the first order ACF for returns are negative and statistically significant, but small in economic terms.[28] This is caused by foreign exchange traders positioning asymmetric quotes, relative to the perceived true market price, so as to attract a single trade on a very specific side of the price, which allows them to manage their inventory positions. As a result, the mid-point of quoted prices tends to move in a fashion similar to that caused by bid-ask bounce (Roll, 1984). This is the spurious movement of asset prices between the bid and ask caused by the execution of trades at both sides of the price, but which is not attributable to the arrival of new information. So as not to distort any patterns in the plots of the five-day ACF's, this first order autocorrelation is excluded. Consistent across the three exchange rates, ACF's for returns shown in the left hand column of Figure 3.3.8.1, are economically small in magnitude and show no discernible pattern.

ACF's for absolute returns, however, show a very distinctive U-shape pattern occupying precisely one day, which repeats continuously. The pattern is robust to all three currencies and is robust to the extension of the correlogram to a lag length of forty days. Figure 3.3.8.2 shows these forty-day correlograms.[29] Each correlogram is dominated by the daily periodic pattern, which causes a severe distortion to the long run pattern. Abstracting from these patterns, however, reveals that the ACF's for absolute five-minute returns appear to decay very rapidly initially, then extremely slowly thereafter. This confirms the findings of Andersen and Bollerslev (1997a, 1997b and 1998a), Bollerslev et al. (2000) and Andersen, Bollerslev and Cai (2000) that ACF's for high frequency absolute returns tend to decay at a hyperbolic rate, indicating that they may represent fractionally integrated time series processes displaying long memory characteristics.

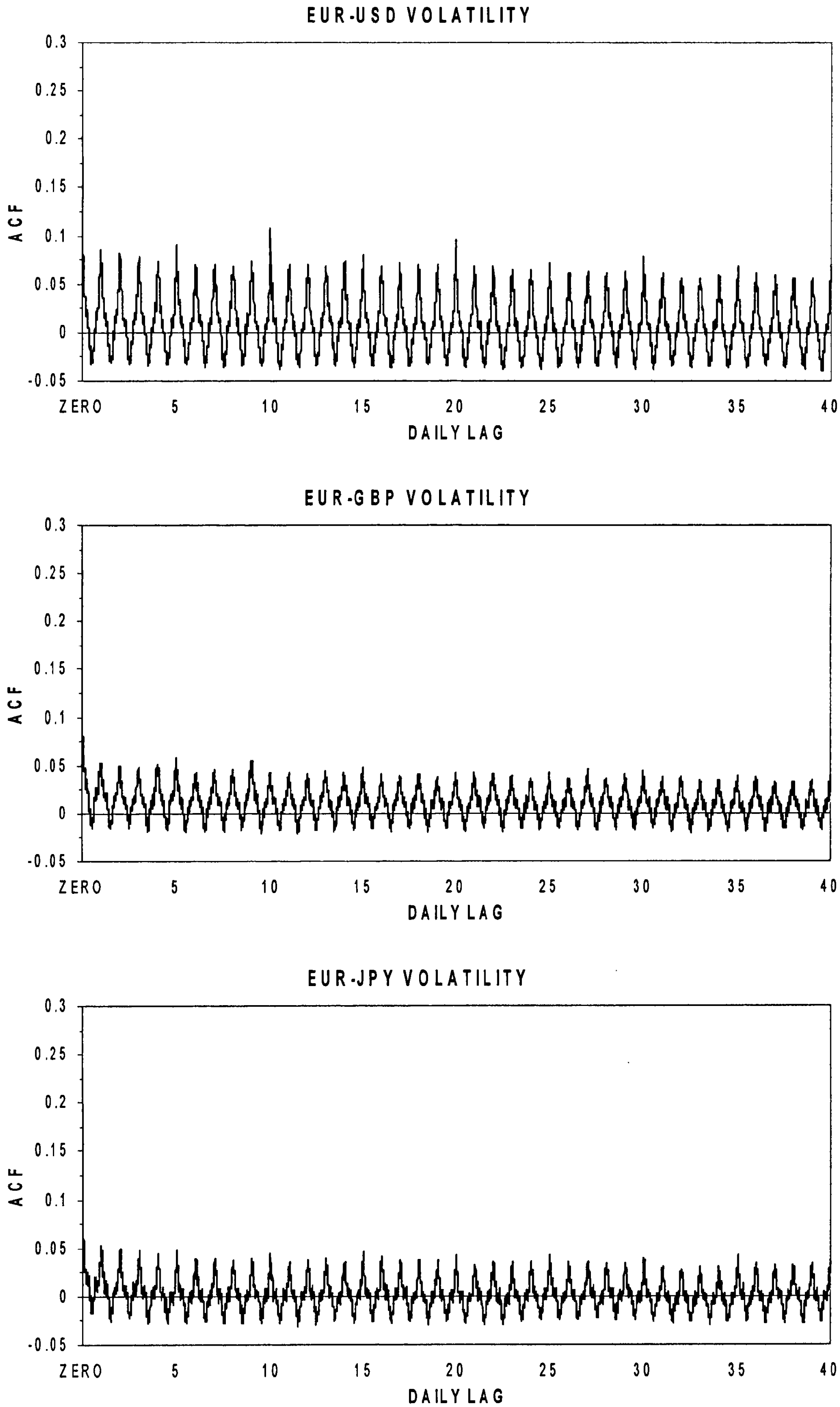
There is a well established literature on fractional integration of time series beginning with applications to the physical sciences in the early 1950's. The interest of econometricians in this area was sparked by Granger and Joyeux (1980) and Hosking (1981).

---

[28] Specifically they are -0.08, -0.19 and -0.11 for EUR-USD, EUR-GBP and EUR-JPY respectively. These are statistically significant when compared with the approximate 5% significance level of 0.01, which is not surprising given the large size of the sample.

[29] A large, negative first order ACF in returns generates a large positive ACF in absolute returns and these are excluded form the plots. The values are 0.18, 0.25 and 0.20 for EUR-USD, EUR-GBP and EUR-JPY respectively.

Figure 3.3.8.2. Forty-Day Correlograms for Five-Minute Absolute Returns.



More recently, there is evidence that long memory processes describe the empirical properties of financial data very well and are successful in modelling both the volatility of asset prices and power transformations of asset returns.[30] As documented by Baillie (1996), the presence of long memory can be defined in terms of the persistence of observed autocorrelations. Autocorrelations take far longer to decay than the exponential rate associated with ARMA models, persistence that is neither consistent with an $I(1)$ process nor an $I(0)$ process. According to Baillie (1996), a particular process, y_t, is said to be integrated of order d, if $(1-L)^d y_t = u_t$, where L is a lag operator, $-0.5<d<0.5$, and u_t is a stationary and ergodic process. For $0<d<0.5$ the process is long memory and its autocorrelation function, ρ_v at lag v, decays at a hyperbolic rate. Specifically, as v approaches infinity, $\rho_v = bv^{2d-1}$ where b is a factor of proportionality, v is the lag length of the ACF, d is the fractional integration parameter, and the implied hyperbolic decay rate is v^{2d-1}.

Time domain procedures for estimating the fractional integration parameter, d, are severely distorted by the presence of strong periodicity in the ACF for absolute returns and also require a strictly positive correlogram. Only after annihilating the daily dependencies does the long memory feature of high frequency returns data clearly stand out. Alternatively, in the presence of the distinct repetitive pattern, semi-parametric, frequency domain procedures that explicitly ignore the intraday periodicities are ideally suited to estimating d and the associated hyperbolic rate of decay. The log-periodogram regression estimator of Geweke and Porter-Hudak (GPH) (1983) has been utilised widely in the literature. Andersen, Bollerslev and Cai (2000) explain that this estimator exploits that if y_t is a long memory process, the spectrum for the process should be linear for frequencies close to zero. If $I(\Lambda_f)$ denotes the sample periodogram at the fth Fourier frequency, by estimating the following log-periodogram regression by OLS:

$$\log[I(\Lambda_f)] = \Delta_0 + \Delta_1 \log(\Lambda_f) + \varepsilon_f, \tag{3.1}$$

[30] See Ding et al. (1993), Ding and Granger (1996), Granger and Ding (1996), Andersen and Bollerslev (1997a, 1997b and 1998a), Andersen, Bollerslev and Cai (2000), Bollerslev et al. (2000) and Bollerslev and Wright (2000). An excellent review of the early literature is provided by Baillie (1996).

where $f=1, 2, \ldots..h$ and h is the square root of the sample size, $\hat{d}$ is calculated as $\hat{d} = -\frac{\hat{\Delta}_1}{2}$. Reisen (1994) offers an alternative semi parametric frequency domain procedure for estimating d that uses a smoothed sample periodogram. Table 3.3.8.1 shows the two alternative estimates for the fractional integration parameter along with their standard errors for each currency. $t\text{-}stat_1$, $t\text{-}stat_2$ and $t\text{-}stat_3$ report test statistics for t tests under varying hypotheses. For $t\text{-}stat_1$ the null hypothesis is that $d=1$ and is rejected in all cases at the 1% level of significance in favour of the one-sided alternative hypothesis that $d<1$. For $t\text{-}stat_2$ the null that $d=0$ is also rejected in all cases at the 1% level in favour of the one-sided alternative that $d>0$. Finally for $t\text{-}stat_3$, the null hypothesis that $d=0.5$ is rejected in all cases at the 1% level in favour of the one sided alternative that $d<0.5$. The very powerful conclusion that can be drawn from this table is that, for each currency, $\hat{d}$ lies between 0 and 0.5 indicating that the three absolute returns series are stationary, fractionally integrated and exhibit long memory.

Figure 3.3.8.3 shows further evidence of the long memory properties of the ACF's for the absolute returns by plotting the sample ACF and the implied hyperbolic rate of decay. This is calculated as,

$$\tilde{\rho}_v = \frac{\Gamma(1-d)}{\Gamma(d)} v^{2d-1}, \tag{3.2}$$

where v denotes the lag length, d is the GPH estimate of the fractional integration parameter and $\Gamma(.)$ is a particular value of the gamma distribution. The ratio of two values of the gamma distribution is the factor of proportionality.[31]

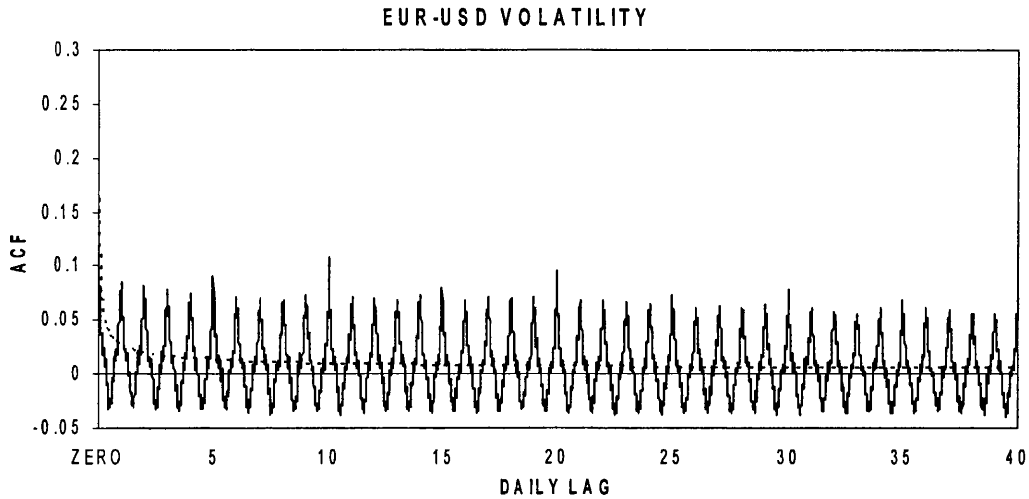
In brief summary, analysis of the long run time series properties of high frequency EUR returns reveals three important features. Firstly, intraday returns contain important information for the understanding of lower frequency return dynamics. Secondly, the autocorrelation functions for return volatility are dominated by a distinct repetitive pattern at the daily frequency, and thirdly that return volatility is a fractionally integrated time series displaying long memory characteristics.

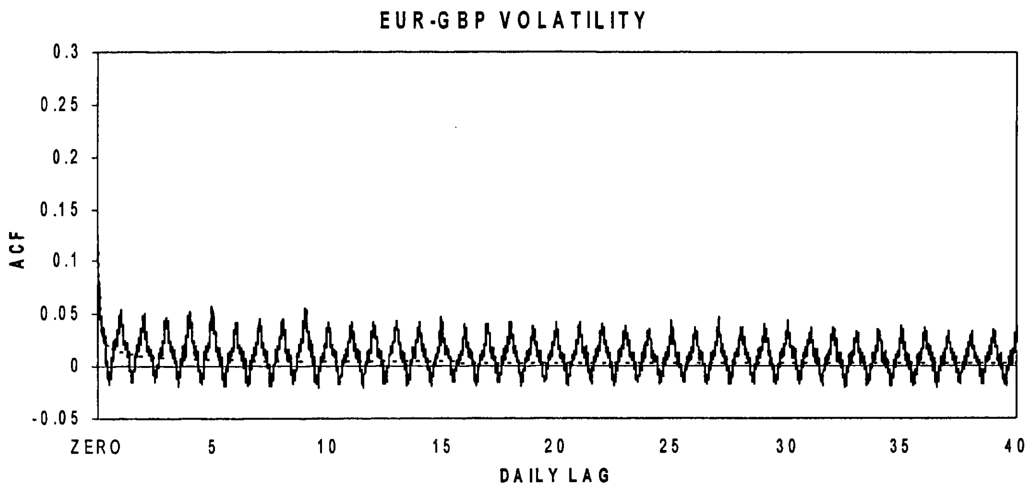
[31] See Granger and Joyeux (1980) for the mathematical details. The GPH estimate of d is chosen arbitrarily when calculating the hyperbolic decay. Analogous plots using the Reisen estimator are available on request.

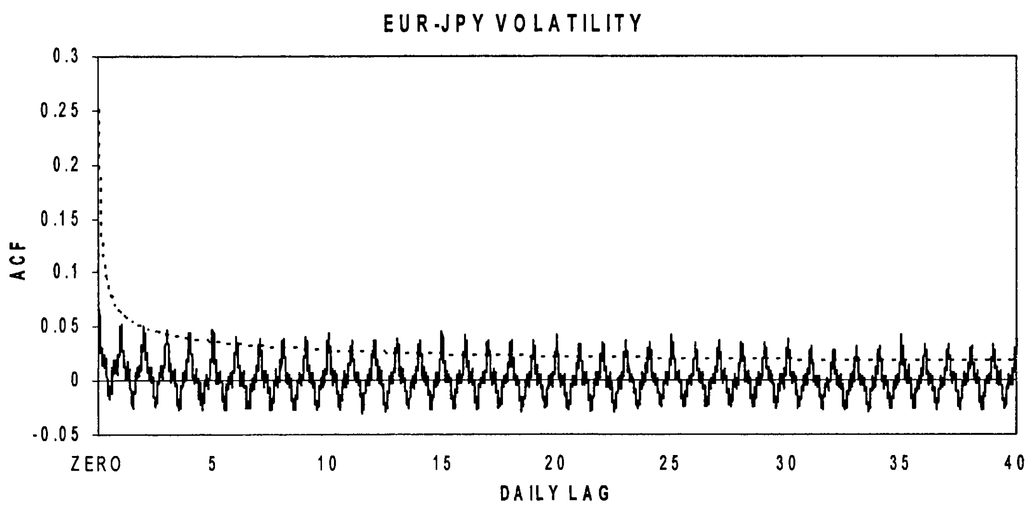
Table 3.3.8.1. Estimates of the Fractional Integration Parameters.

		GPH	REISEN
EUR-USD	$\hat{d}$	0.2685	0.3041
	se	0.0357	0.0205
	$t\text{-}stat_1$	-20.4635	-34.0019
	$t\text{-}stat_2$	7.5117	14.8567
	$t\text{-}stat_3$	-6.4759	-9.5726
EUR-GBP	$\hat{d}$	0.2244	0.2414
	se	0.0357	0.0205
	$t\text{-}stat_1$	-21.6981	-37.0626
	$t\text{-}stat_2$	6.2771	11.7959
	$t\text{-}stat_3$	-7.7105	-12.6334
EUR-JPY	$\hat{d}$	0.3207	0.3321
	se	0.0357	0.0205
	$t\text{-}stat_1$	-19.0027	-32.6345
	$t\text{-}stat_2$	8.9725	16.2240
	$t\text{-}stat_3$	-5.0151	-8.2053

Figure 3.3.8.3. Forty Day Correlograms for Absolute Returns with Implied Hyperbolic Decay.







Importantly, these features imply that standard ARCH, GARCH and stochastic volatility models are ill-suited for modelling such pronounced periodic patterns and long run dependencies.

3.4 ECONOMETRIC MODELLING

As identified in section 3.3, the volatility dynamics of high frequency foreign exchange returns are characterised by pronounced intraday patterns, highly significant short lived announcement effects, and long memory properties. In the modelling procedure adopted here, which follows Andersen and Bollerslev (1998a), the volatility process is driven by the simultaneous interaction of these components associated with predictable calendar effects, macroeconomic news announcements and a potentially persistent, unobserved latent factor. The procedure allows standard regression techniques to be used to simultaneously account for each separate component of volatility with the objective of isolating the dynamic behaviour of volatility around macroeconomic news announcements. In full generality, the model takes the following form,

$$R_{t,n} - \overline{R}_{t,n} = \sigma_{t,n} \cdot s_{t,n} \cdot Z_{t,n}, \qquad (3.3)$$

where $\overline{R}_{t,n}$ is the expected five-minute return such that $R_{t,n} - \overline{R}_{t,n}$ measures excess returns, $Z_{t,n}$ is an independent and identically distributed zero mean, and unit variance error term, $s_{t,n}$ represents the intraday pattern, calendar features and macroeconomic announcement effects, and $\sigma_{t,n}$ denotes the remaining latent volatility component conventionally captured by ARCH or stochastic volatility models. All volatility components are assumed to be independent and non-negative.

The components of equation (3.3) are not separately identifiable without additional restrictions. Squaring and taking logs allows $s_{t,n}$ to be isolated as the sole explanatory variables,

$$2\log\left[\left|R_{t,n} - \overline{R}_{t,n}\right|\right] - \log\sigma_{t,n}^2 = \mu_0 + 2\log s_{t,n} + u_{t,n}, \qquad (3.4)$$

where $c = E[\log Z_{t,n}^2]$ and $u_{t,n} = \log Z_{t,n}^2 - E[\log Z_{t,n}^2]$. Since each particular macroeconomic news announcement is unique, $\log s_{t,n}$ will be stochastic. The price and volatility reaction will reflect the news content (the innovation relative to consensus forecasts) of the announcement, the dispersion of beliefs among traders and other market conditions at the time of the release. To capture these dynamic features directly, it would be necessary to model a wide information set including expectations and recent return innovations, for example, amongst other factors. To maintain simplicity at the outset, the (log) volatility response, conditional on the type of announcement, the time of release and other relevant calendar information, is merely assumed to have a well defined expected value, $E[\log s_{t,n}]$. This average impact is governed by purely deterministic regressors such that the innovation resulting from a new release, $\log s_{t,n} - E[\log s_{t,n}]$ can be isolated. The final restriction is that $\log \sigma_{t,n}$ is strictly stationary and has a finite unconditional mean, $E[\log \sigma_{t,n}]$.

To obtain an operational regression equation, Andersen and Bollerslev (1998a) impose some additional structure. First, $\overline{R}_{t,n}$ is assumed constant and well approximated by the sample mean, $\overline{R}$, which is an innocuous assumption given that the standard deviation dwarfs the mean return, implying that inferences are not sensitive to minor misspecification of the conditional mean. Second, to help control for systematic volatility movements caused by the latent volatility component, an a priori estimate of the return standard deviation, $\hat{\sigma}_{t,n}$, is applied. Third, a parametric representation is imposed on the regressor $E[\log s_{t,n}]$ which accounts for calendar and announcement effects. Since theory provides no guidelines regarding the shape of the intraday pattern, two adaptive functional forms, a Fourier flexible form (FFF) and a cubic spline, are chosen as alternatives. A benefit to these approaches is that they use the entire span of data in fitting the intraday pattern, rather than relying on the intraday average absolute returns. [32] The operational regression then becomes:

[32] It is possible to remove the intraday volatility pattern in returns by filtering absolute, de-meaned returns by the mean absolute return for a particular interval as plotted in Figure 3.3.2.2 (see Andersen and Bollerslev, 1997b). However, this technique does not allow a sufficiently accurate separation of volatility spikes from the underlying intraday pattern since the mean absolute return for intervals immediately following a macroeconomic announcement will be high and the very effect that is to be investigated is filtered away. Preference is therefore given to the FFF approach advocated by Andersen and Bollerslev (1998a), Andersen, Bollerslev and Cai (2000) and Bollerslev et al. (2000) and to the cubic spline approach advocated by Taylor (2004).

$$2\log\frac{|R_{t,n}-\overline{R}|}{\hat{\sigma}_{t,n}} = \hat{\mu}_0 + E[\log s_{t,n}] + \hat{u}_{t,n}, \tag{3.5}$$

where $\hat{c} = E[\log Z_{t,n}^2] + E[\log\sigma_{t,n}^2 - \log\hat{\sigma}_{t,n}^2]$, the error process $\hat{u}_{t,n}$ is stationary and E[log$s_{t,n}$] represents the choice of parametric function that models the intraday volatility pattern, calendar features and announcement effects. Two important empirical features of this regression are that the use of de-meaned, five-minute returns annihilates the problem of returns with a value of zero and the log transformation eliminates any extreme outliers, rendering the regression more robust.

The potentially highly persistent volatility component, $\hat{\sigma}_{t,n}$, is estimated as follows. Daily volatility, σ_t, is estimated from GARCH models applied to a longer series of daily returns from 2nd January 1999 to 31st July 2003. Firstly, based on the temporal dependencies and long memory properties evidenced in section 3.3.4, a fractionally integrated MA(1)-FIGARCH(1,d,1) model is implemented, which follows the approach of Bollerslev et al. (2000). As a robustness check, a simple MA(1)-GARCH(1,1) model is also used for its simplicity and popularity and this follows the approach of Andersen and Bollerslev (1998a). Specifically, both models specify a first order moving average process for the mean daily return:

$$R_t = \phi_0 + \phi_1\varepsilon_{t-1} + \varepsilon_t. \tag{3.6}$$

While the conditional variance equations are then given by, respectively:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \left[1-\beta_1 L - (1-\varphi L)(1-L)^d\right]\varepsilon_t^2, \tag{3.7}$$

$$\sigma_{t,G}^2 = \omega + \beta\sigma_{t-1}^2 + \psi\varepsilon_t^2. \tag{3.8}$$

FI denotes the FIGARCH(1,d,1) conditional variance model of equation (3.7) where L represents the lag operator and d is the fractional integration parameter and G

references the simple GARCH(1,1) model of equation (3.8).[33] Assuming that this volatility component is constant over the trading day, the associated intraday estimates are:

$$\hat{\sigma}_{t,n,g} = \hat{\sigma}_{t,g} / N^{1/2}, \tag{3.9}$$

where $N=288$ represents the number of five-minute intervals during a trading day and $g=FI$ or G separates the daily volatility factors modelled using the MA(1)-FIGARCH(1,d,1) and MA(1)-GARCH(1,1) specifications in (3.7) and (3.8), respectively. Standardisation of the de-meaned absolute returns by $\hat{\sigma}_{t,n,g}$ allows the volatility factor on the left hand side of (3.5) to vary over time thus improving the efficiency of the estimation, and is likely to eliminate the volatility clustering and high persistence that is prevalent in financial data at the daily frequency. It is important to recognise, though, that this procedure may give rise to a generated regressors problem which may impart a bias to standard errors. To address this issue the time-varying estimates calculated from equations (3.7) and (3.8) are also compared to a constant daily volatility factor, which is free of any generated regressor problem, calculated as:

$$\hat{\sigma}_{t,n,\bar{g}} = \overline{\sigma}_g / N^{1/2}, \tag{3.10}$$

where $\overline{\sigma}_g$ denotes the sample mean of $\hat{\sigma}_{t,g}$ and $\bar{g}$ clarifies that this estimator is based on the sample mean of $\hat{\sigma}_{t,g}$.

The objective of this study is to concentrate on macroeconomic news announcement effects, so the specification imposed on the regressor E[log$s_{t,n}$] in order to annihilate the intraday volatility pattern is very important. Two alternative techniques designed to adapt well to the intraday pattern are compared in this chapter. Firstly, following Andersen and Bollerslev (1998a), the FFF specification is defined as follows

[33] Estimation results for these conditional variance models are not shown for brevity and in order to maintain the focus of this study on macroeconomic announcement effects, but they are available on request.

$$E[\log s_{t,n}] = \mu_1 + \sum_{k=1}^{K} \lambda_k \cdot I_k(t,n) + \sum_{q=1}^{Q} \left(\delta_{\cos,q} \cdot \cos \frac{q2\pi}{N} n + \delta_{\sin,q} \cdot \sin \frac{q2\pi}{N} n \right), \qquad (3.11)$$

where $I_k(t, n)$ is an indicator for the event k occurring during interval n on day t and μ_0, λ_k, $\delta_{cos,q}$ and $\delta_{sin,q}$ are the fixed coefficients to be estimated. This expression is non-linear in the intraday time interval, n, parameterised by a number of sinusoids that occupy precisely one day and a set of event dummies, I_k. Q is a tuning parameter and refers to the order of expansion. $Q=4$ was selected based on the significance of estimated coefficients, the Akaike Information Criteria (AIC) and the success of the model in fitting the intraday volatility pattern. This supports the evidence of Andersen and Bollerslev (1998a). In the absence of the event dummies, equation (3.11) reduces to the conventional Fourier flexible form (FFF). During periods of daylight saving time the sinusoids are translated leftwards by one hour using a time deformation procedure.

The second characterisation of the intraday volatility pattern uses a cubic spline specification, whereby, as recently been advocated by Taylor (2004), a series of third order polynomials are fitted between clearly defined knots during the day:

$$E[\log s_{t,n}] = \mu_1 + \sum_{k=1}^{K} \lambda_k \cdot I_k(t,n) + \sum_{m=1}^{M} \left[\alpha_{1,m} D_m \left(\frac{n-l_m}{N} \right) + \alpha_{2,m} D_m \left(\frac{n-l_m}{N} \right)^2 + \alpha_{3,m} D_m \left(\frac{n-l_m}{N} \right)^3 \right]. \qquad (3.12)$$

l_m denotes the interval of the day in which knot m ($m=1,2,...,M$) is placed, and these are chosen a priori based on the underlying intraday pattern, D_m are dummy variables taking the value 1 if $n \geq l_m$ and 0 otherwise and $\alpha_{1,m}$, $\alpha_{2,m}$ and $\alpha_{3,m}$ are coefficients to be estimated. In light of the twenty-four hour intraday volatility pattern, there are five knots in total ($M=5$). The first knot is positioned at interval 0 (21:00 GMT), $l_1=0$, corresponding to the start of the trading day, and $l_2=36$ (00:00 GMT) such that the second knot corresponds to the opening of markets in Tokyo. A cubic spline is therefore fitted to the volatility pattern between the opening of trading in Sydney and Tokyo demonstrating that the knots are not chosen arbitrarily, but are chosen to reflect the geographical nature of the foreign exchange market that drives the distinctive intraday volatility pattern. Thus $l_3=96$ (5:00GMT) in winter to capture the volatility slowdown before the onset of early trading in Europe and this is shifted leftwards by one hour during DST ($l_3=84$ corresponding to 4:00 GMT). Similarly, $l_4=132$ during winter and 120 during DST (8:00 and 7:00 GMT, respectively) to position the fourth knot at the volatility peak occurring at the overlap of trading in Japan, Europe and the UK, and finally, $l_5=216$ in winter and 204 in DST (15:00 and 14:00 GMT) at the highest point of the intraday pattern.

The $I_k(t, n)$ regressors in equations (3.11) and (3.12) indicate dummy variables associated with holidays, weekdays, calendar related characteristics and macroeconomic news announcements. Holiday dummies refer to regional holidays that cause volatility slowdowns but still provide reliable quotes and returns, and they only affect the portion of the trading day corresponding to the trading activity of the financial centre affected by the holiday and intervals during these holiday periods are assigned a value of unity (zero otherwise) to capture explicitly their effect. Similar simple dummy variables are also included for each day of the week to account for any systematic weekly patterns in exchange rate volatility. Based on the analysis of section 3.3.2 and the plots in Figure 3.3.2.2 in particular, a DST dummy is also included to allow for systematically higher volatility during DST such that intervals occurring during DST are assigned a value of unity and zero otherwise.

The remaining calendar related characteristics refer to volatility jumps at the opening of markets in Tokyo and Hong Kong, Singapore and Malaysia, and volatility slowdowns surrounding weekends, especially during periods of DST. To account properly for these calendar effects whilst maintaining the smooth cyclical periodicity of the intraday volatility pattern, a polynomial structure is imposed on the volatility response for these events. In full generality, if an event affects volatility from time t_0 to time $t_o+\Omega$, the impact on volatility can be represented over the event window $\tau=0,1.....\Omega$ by a polynomial specification:

$$p(\tau) = c_0 + c_1\tau + ... + c_P\tau^P \quad . \tag{3.13}$$

As argued by Andersen, Bollerslev, Diebold and Vega (2003), the use of lower ordered polynomials constrains the volatility response in helpful ways: by promoting parsimony, by retaining flexibility of approximation and by facilitating the imposition of sensible constraints on the response pattern. Specifically, enforcing $p(0)=0$ ensures there is no jump in volatility away from the underlying intraday pattern and $p(\Omega)=0$ enforces the requirement that the impact effect slowly fades to zero. The latter constraint gives rise to a polynomial with one less parameter:

$$p(\tau) = c_0[1-(\tau/\Omega)^P] + ... + c_1\tau[1-(\tau/\Omega)^{P-1}] + c_{P-1}\tau^{P-1}[1-(\tau/\Omega)]. \quad (3.14)$$

Based on the intraday patterns presented in section 3.3, the Tokyo opening effect is afforded a linear response ($P=1$) beginning at 00:05 GMT and lasting until 00:30 GMT ($\Omega=6$) with the effect fading to zero at 00:35 GMT ($p(\Omega)=0$). Identical structure applies to the Hong Kong, Singapore and Malaysia opening effect but the effect begins an hour later at 01:05 GMT. To account for a Monday morning slowdown, when traders in Sydney and Wellington are the only participants active in the market, a second order polynomial ($P=2$) is imposed from 21:05 GMT to 23:00 GMT ($\Omega=23$) with the restriction that $p(\Omega)=0$ ensuring the effect fades to zero. Similarly, a Friday night slowdown, when US traders are the only active group, is also modelled by a second order polynomial. Based on the plots of section 3.3, this effect begins at 17:05 GMT in winter time and lasts until 21:00 GMT ($\Omega=47$) with the start of the effect shifted by one hour to 16:05 GMT ($\Omega=59$) during DST. For this polynomial the restriction that $p(0)=0$ ensures that there is no step away from the intraday pattern at the impact of the event. The leftward shift of the intraday pattern by one hour during DST gives rise to a hiatus between close of trading in the US and the opening of trading in Wellington and this is accommodated by a second order polynomial for each day during DST beginning at 19:05 GMT and lasting until 21:00 GMT ($\Omega=23$) with the restrictions $p(\Omega)=0$ and $p(0)=0$ imposed. The final calendar effect is a winter slowdown which occurs for EUR-USD only. Figure 3.3.3.1 shows that volatility tends to be lower in the early part of the trading day for winter days and this effect is accounted for by a second order polynomial beginning at 21:05 GMT on days during the winter time and lasting until 00:00 GMT ($J=35$). The effect of the winter slowdown polynomial is restricted to reach zero at 00:00 GMT ($p(\Omega)=0$).

Volatility response patterns for macroeconomic news announcements require further experimentation to discover the most accurate and appropriate response dynamics and horizons. Given the limited number of occurrences of each type of news announcement and the inherent noise in the return process, it is inefficient and infeasible to estimate accurately separate coefficients for dummies for each five-minute interval before, immediately after and following each news release. Rather, a reasonable decay structure is imposed. The evidence in Figures 3.3.7.1 to 3.3.7.8 suggest a violent reaction in volatility following some US announcements, which can take up to one hour to decay, and possibly the existence of elevated volatility in the intervals just prior to the announcement. To test explicitly for these dynamics, equation (3.5) is estimated using the alternative specifications (3.11) and (3.12) for the intraday pattern, using $\hat{\sigma}_{t,n,FI}$ as the latent volatility factor and including the calendar polynomials described above. News announcements are grouped by country with three indicator variables included in equation (3.5) for each country referenced by $I_{c,w}(t, n)$. This is a dummy variable relating to an announcement for country c occurring during interval n on day t taking the value unity during period w and zero otherwise, where w refers to an event window: a pre-announcement period ($w=1$), a period just after the announcement ($w=2$) and a post announcement period ($w=3$). The observation windows are equal to fifteen minutes before the announcement ($w=1$), five minutes just after the announcement ($w=2$) and the following twenty five minutes after the announcement ($w=3$). The estimated $\lambda_{c,w}$ coefficients reported in Table 3.4.1 measure the volatility response during the three event windows with a total of three coefficients estimated for each of the six countries.[34]

The evidence in Table 3.4.1 shows that the most dramatic reaction of volatility, across all three exchange rates, occurs in response to US macroeconomic news. This confirms the graphical evidence of Figures 3.3.7.1 to 3.3.7.8, but the more robust econometric test evidence presented in Table 3.4.1 reveals that, on average, Eurozone, German and UK news also cause a reaction in exchange rate volatility. The majority of the reaction in volatility occurs after the announcement, as shown by the statistical significance of coefficients for event windows $w=2$ and $w=3$. Coefficients for the event window preceding announcements are only statistically significant for Eurozone news and for EUR-USD and EUR-GBP. Although these coefficients are statistically greater than zero, they are small in economic terms with only 0.65 times the usual volatility added during this event window preceding the release of Eurozone news.

[34] Table 3.4.1 shows only the news announcement coefficient estimates and their robust t statistics since the purpose of this analysis is to derive a suitable volatility response pattern for individual macroeconomic announcements.

Table 3.4.1. Volatility Dynamics Surrounding Announcements.

	FFF			CUBIC SPLINE		
COEFFICIENT	EUR-USD	EUR-GBP	EUR-JPY	EUR-USD	EUR-GBP	EUR-JPY
$\lambda_{US,\,1}$	0.0784	0.0902	0.1179	-0.0223	0.0154	0.0508
	(0.9284)	(0.8532)	(1.2991)	(-0.2748)	(0.1484)	(0.5805)
$\lambda_{US,\,2}$	**1.2736****	**0.7734****	**0.7588****	**1.2780****	**0.7814****	**0.7729****
	(9.6794)	(4.8669)	(5.7520)	(9.7442)	(4.9180)	(5.8952)
$\lambda_{US,\,3}$	**0.4142****	**0.3041****	**0.2443****	**0.3151****	**0.2566****	**0.2560****
	(5.2814)	(3.4723)	(3.1083)	(4.3117)	(3.0262)	(3.4614)
$\lambda_{EU,\,1}$	**0.3366****	**0.3899****	0.1138	**0.2799****	**0.3139***	0.0661
	(2.8362)	(2.8101)	(0.9372)	(2.4339)	(2.1912)	(0.5512)
$\lambda_{EU,\,2}$	**0.3463***	**0.3855***	**0.3992***	**0.3685***	**0.4388***	**0.4074***
	(1.7821)	(1.6673)	(2.0029)	(1.8975)	(1.9104)	(2.0430)
$\lambda_{EU,\,3}$	**0.2210***	**0.3599***	**0.1777***	0.1551	**0.3087****	0.1553
	(2.0918)	(2.9745)	(1.6765)	(1.5266)	(2.6497)	(1.4267)
$\lambda_{GER,\,1}$	-0.0311	-0.1732	-0.1048	-0.0492	-0.1926	-0.1243
	(-0.2683)	(-1.2844)	(-0.8712)	(-0.4296)	(-1.3661)	(-1.0348)
$\lambda_{GER,\,2}$	**0.3498***	0.2126	0.0897	**0.3789***	0.1878	0.0887
	(2.0311)	(0.9990)	(0.4421)	(2.1856)	(0.8751)	(0.4380)
$\lambda_{GER,\,3}$	**0.2263****	**0.1863***	0.0725	**0.2196****	0.1574	0.1308
	(2.7395)	(1.7847)	(0.7747)	(2.6388)	(1.4800)	(1.4594)
$\lambda_{FRA,\,1}$	0.1810	0.1800	0.0976	0.0661	0.0800	-0.0043
	(1.5618)	(1.3578)	(0.7863)	(0.5787)	(0.6125)	(-0.0366)
$\lambda_{FRA,\,2}$	0.0850	0.0628	0.0438	-0.1007	-0.1268	-0.0631
	(0.4194)	(0.2438)	(0.2268)	(-0.4862)	(-0.4859)	(-0.3164)
$\lambda_{FRA,\,3}$	0.0660	-0.0187	0.0801	0.0439	-0.1005	0.0468
	(0.7171)	(-0.1584)	(0.7348)	(0.4293)	(-0.7847)	(0.4023)
$\lambda_{UK,\,1}$	-0.0628	-0.2270	-0.0072	-0.0221	-0.2018	-0.0093
	(-0.5902)	(-1.4633)	(-0.0581)	(-0.2097)	(-1.3179)	(-0.0753)
$\lambda_{UK,\,2}$	0.0847	**0.7870***	-0.2310	0.1754	**0.8657****	-0.1682
	(0.4698)	(3.2920)	(-1.1177)	(0.9738)	(3.6235)	(-0.8143)
$\lambda_{UK,\,3}$	**0.2182***	0.1485	**0.1808***	**0.1912***	**0.1956***	**0.1975***
	(2.1780)	(1.2636)	(1.7812)	(1.9772)	(1.7170)	(1.9367)
$\lambda_{JAP,\,1}$	0.0473	0.2575	-0.1317	0.0006	**0.2780***	-0.1092
	(0.3733)	(1.5831)	(-0.8931)	(0.0045)	(1.6769)	(-0.7629)
$\lambda_{JAP,\,2}$	0.0488	-0.1029	0.1211	-0.0109	-0.0737	0.0890
	(0.2607)	(-0.3814)	(0.5993)	(-0.0582)	(-0.2718)	(0.4372)
$\lambda_{JAP,\,3}$	0.0830	-0.1726	0.0219	0.1403	0.0418	0.0182
	(0.7437)	(-1.2056)	(0.1752)	(1.2739)	(0.3105)	(0.1536)

Notes: The table shows coefficient estimates and their associated Newey-West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) robust t statistics in parentheses obtained from the estimation of equation (3.5) using $\hat{\sigma}_{t,n,FI}$ and including all relevant calendar event polynomials. The table reports only the coefficient estimates for the news announcement indicator variables, $\lambda_{c,w}$, for each country (c) and event window (w). The event windows are fifteen minutes prior to an announcement ($w=1$), five minutes immediately after an announcement ($w=2$) and the following twenty five minutes after the announcement ($w=3$). ** and * show coefficients significantly positive at the 1 and 5% level of significance, respectively.

This response is almost certainly due to volatility surrounding a single announcement: interest rate decisions by the ECB.[35]

The evidence presented in Figures 3.3.7.1 to 3.3.3.8 and Table 3.4.1 confirms the findings of Andersen and Bollerslev (1998a), Andersen, Bollerslev and Cai (2000) and Bollerslev et al. (2000) that the average volatility dynamics in response to macroeconomic news announcements are well approximated by a third order polynomial restricted to equal zero at the end of the response horizon, as represented by:

$$\lambda(k,\tau) = \lambda_k \cdot p(\tau), \tag{3.15}$$

where k refers to the event type and $p(\tau)$ dictates the response at lag $i=0, 1, 2, \ldots, 12$ and is itself determined by:

$$p(\tau) = c_0[1-(\tau/12)^3] + c_1\tau[1-(\tau/12)^2] + c_2\tau^2[1-(\tau/12)]. \tag{3.16}$$

This is precisely the same polynomial as equation (3.14), but specifies $P=3$ and $\Omega=12$. For initial estimation, given the dominance of US news in Figures 3.3.7.1 to 3.3.7.8 and Table 3.4.1, only US news is controlled for. Each announcement has a fixed response horizon of one hour ($\Omega=12$) except interest rate announcements from the FOMC and the Employment Report, which are afforded a two hour horizon based on further analysis of their influence in the plots for real output and interest rate news in Figure 3.3.7.3. To calculate this elongated two hour response whilst retaining the benchmark pattern, the τ variable is allowed to progress only by a (12/24) fraction of a unit per five-minute interval, rather than a full unit. This time deformation technique stretches the event time scale so that it conforms to the desired horizon. The pattern for $p(\tau)$ is calibrated by fitting the three parameters, c_0, c_1 and c_2, for all US announcements combined in equation (3.5) estimated without λ_k

[35] Since the reaction of exchange rate volatility to macroeconomic announcements occurs after the news release, and since the only reaction in the pre-announcement event window only occurs for Eurozone news, is relatively weak in terms economic significance and is likely caused by a single announcement, the pre-announcement period does not warrant inclusion in the explicit modelling of the news response pattern. The rise in volatility pre-announcement apparent from the plots in Figures 3.3.7.1 to 3.3.7.8 disappears when controlling for the intraday pattern.

coefficient, using $\hat{\sigma}_{t,n,FI}$ for the latent volatility component. The parameters are allowed to vary across exchange rates and both intraday filters giving six different estimates for each coefficient. The response pattern is then fixed according to these estimates, leaving λ_k as the only free parameter to be estimated, which measures the degree to which the event loads onto this pattern. Table 3.4.2 displays the coefficient estimates.

3.5 EMPIRICAL RESULTS

3.5.1 Intraday Volatility Modelling

Table 3.5.1.1 shows the estimated coefficients and their robust t statistics for equation (3.5). The left-hand side variable measures logarithmic-squared, standardised absolute de-meaned returns. The right-hand side variables represent the deterministic calendar and announcement regressors. The FFF and cubic spline functions represented by equations (3.11) and (3.12) provide alternative ways to capture the intraday volatility pattern, which readily accommodate the leftward shift in the pattern by one hour during DST. The $I_k(t,n)$ variables indicate either simple dummy variables or more elaborate pre-determined volatility response patterns associated with calendar and announcement effects.

A simple dummy variable (denoted as 'Summer' in the tables) accounts for the possibility of systematically higher volatility during DST and a restricted second order polynomial, giving rise to the estimation of two parameters, allows for a volatility slowdown between 19:00 and 21:00 GMT on days falling in DST. A separate, restricted linear volatility decay is implemented for the opening of markets in Tokyo ('Tokyo' in the tables), lasting from 00:00 GMT to 00:30 GMT and for the opening of markets in Hong Kong, Singapore and Malaysia (termed 'Hong Kong' in the tables). Second order polynomials are included to account for a volatility slowdown around weekends with 'Monday Early' capturing a slowdown from 21:00 to 23:00 GMT on Mondays in the Pacific zone and 'Friday Late' accounting for lower volatility during the North American trading segment on Fridays from 17:00 to 21:00 GMT during winter time and from 16:00 to 21:00 GMT during DST. A restricted second order polynomial is also included from 21:00 to 00:00 GMT during winter time ('Winter Slowdown') for EUR-USD. Trading periods affected by regional holidays and weekday effects are captured by simple dummy variables.

Table 3.4.2. Estimated Coefficients for Volatility Response Patterns.

	FFF			SPLINE		
COEFFICIENT	EUR-USD	EUR-GBP	EUR-JPY	EUR-USD	EUR-GBP	EUR-JPY
c_0	1.2206	0.6387	0.6994	1.2498	0.6625	0.7224
c_1	-0.4166	-0.1043	-0.2199	-0.4093	-0.1100	-0.2258
c_2	0.0555	0.0048	0.0304	0.0543	0.0065	0.0319

Notes: The table shows the estimated coefficients of the volatility response pattern specified in equation (3.16) applied to all US news combined in equation (3.5). The estimation includes all relevant calendar effects and uses $\hat{\sigma}_{t,n,FI}$ as the latent volatility factor. Coefficients are allowed to vary across currencies and intraday volatility models in order to detect any differences in volatility responses.

Table 3.5.1.1. Intraday Patterns and Calendar Effects Using MA(1)-FIGARCH(1,d,1) Daily Volatility Factor.

Panel (A) Intraday Patterns							
		FFF				SPLINE	
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
$\hat{\mu}_0 + \mu_1$	**-2.470**	**-2.271**	**-2.377**	$\hat{\mu}_0 + \mu_1$	**-3.057**	**-2.845**	**-2.943**
	(-50.23)	(-42.15)	(-45.10)		(-17.41)	(-14.00)	(-17.11)
$\delta_{cos,1}$	**-0.277**	**-0.229**	**-0.212**	$\alpha_{1,1}$	8.397	12.453	12.530
	(-10.70)	(-7.94)	(-7.65)		(0.89)	(1.05)	(1.28)
$\delta_{cos,2}$	**-0.090**	**0.078**	-0.043	$\alpha_{2,1}$	-313.50	-193.63	-298.74
	(-3.54)	(2.74)	(-1.57)		(-1.93)	(-0.95)	(-1.74)
$\delta_{cos,3}$	**-0.287**	**-0.277**	**-0.289**	$\alpha_{3,1}$	**2167.3**	875.28	**1943.5**
	(-11.79)	(-9.92)	(-10.88)		(2.69)	(0.88)	(2.29)
$\delta_{cos,4}$	**0.116**	0.036	0.040	$\alpha_{1,2}$	**-36.196**	-11.571	**-35.649**
	(4.99)	(1.34)	(1.56)		(-4.52)	(-1.25)	(-4.41)
$\delta_{sin,1}$	**-0.607**	**-0.649**	**-0.431**	$\alpha_{2,2}$	**-488.62**	-114.77	**-415.10**
	(-24.05)	(-22.76)	(-15.59)		(-3.39)	(-0.66)	(-2.75)
$\delta_{sin,2}$	**-0.133**	0.005	0.017	$\alpha_{3,2}$	**-2173.4**	-888.90	**-1953.7**
	(-5.41)	(0.19)	(0.65)		(-2.69)	(-0.89)	(-2.30)
$\delta_{sin,3}$	**0.144**	**0.159**	**0.098**	$\alpha_{1,3}$	4.876	3.355	-1.244
	(6.00)	(5.93)	(3.79)		(0.83)	(0.47)	(-0.19)
$\delta_{sin,4}$	**-0.110**	-0.046	**-0.095**	$\alpha_{2,3}$	115.09	183.27	**261.55**
	(-4.77)	(-1.76)	(-3.84)		(1.05)	(1.37)	(2.13)
				$\alpha_{3,3}$	-400.06	-871.82	**-1289.8**
					(-0.68)	(-1.23)	(-1.96)
				$\alpha_{1,4}$	**-26.178**	-15.903	-8.322
					(-3.52)	(-1.84)	(-0.98)
				$\alpha_{2,4}$	76.329	159.28	236.05
					(0.70)	(1.22)	(1.92)
				$\alpha_{3,4}$	382.35	873.40	1292.0
					(0.64)	(1.21)	(1.93)
				$\alpha_{1,5}$	-8.276	1.635	0.789
					(-1.79)	(0.33)	(0.16)
				$\alpha_{2,5}$	**-96.099**	**-110.10**	**-98.151**
					(-3.73)	(-3.83)	(-3.58)
				$\alpha_{3,5}$	**179.38**	**231.32**	**202.98**
					(2.24)	(2.59)	(2.38)

Table 3.5.1.1. (Continued)

Panel (B) Calendar Effects							
		FFF				SPLINE	
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
Tokyo	**0.504**	**0.484**	**0.633**	Tokyo	0.215	**0.456**	**0.398**
	(4.19)	(3.13)	(5.08)		(1.65)	(2.66)	(2.94)
Hong Kong	0.224	0.230	**0.431**	Hong Kong	**0.224**	0.278	**0.458**
	(1.93)	(1.55)	(3.65)		(1.99)	(1.91)	(4.03)
Holiday	**-0.258**	-0.034	-0.096	Holiday	**-0.257**	-0.027	-0.092
	(-4.02)	(-0.46)	(-1.39)		(-4.01)	(-0.37)	(-1.33)
US News	**1.000**	**1.000**	**1.000**	US News	**1.000**	**1.000**	**1.000**
	(9.92)	(5.49)	(5.74)		(10.21)	(5.71)	(5.98)
Monday	-0.195	0.108	-0.275	Monday	-0.291	0.190	-0.351
Early	(-0.80)	(0.43)	(-1.06)	Early	(-1.15)	(0.66)	(-1.23)
	0.036	0.058	-0.007		0.037	0.030	-0.007
	(0.79)	(1.28)	(-0.15)		(0.77)	(0.57)	(-0.15)
Friday	-0.010	-0.001	-0.011	Friday	-0.009	0.001	-0.007
Late	(-0.88)	(-0.07)	(-0.87)	Late	(-0.75)	(0.08)	(-0.54)
	0.000	0.000	0.000		0.000	0.000	0.000
	(0.89)	(0.54)	(1.32)		(0.81)	(0.42)	(0.95)
Winter	**-0.429**			Winter	**-0.526**		
Slowdown	(-2.36)			Slowdown	(-2.48)		
	0.021				0.031		
	(0.96)				(1.26)		
Summer	**-0.045**	-0.016	0.001	Summer	-0.032	-0.015	-0.014
Slowdown	(-2.39)	(-0.72)	(0.06)	Slowdown	(-1.47)	(-0.57)	(-0.59)
Summer	**0.202**	**0.131**	**0.103**	Summer	**0.217**	**0.150**	0.071
	(5.55)	(3.33)	(2.69)		(3.15)	(2.19)	(1.09)
Tuesday	**0.350**	**0.304**	**0.329**	Tuesday	**0.344**	**0.300**	**0.325**
	(6.34)	(4.97)	(5.59)		(6.25)	(4.89)	(5.50)
Wednesday	**0.165**	0.088	0.120	Wednesday	**0.160**	0.085	0.116
	(2.53)	(1.23)	(1.68)		(2.46)	(1.18)	(1.62)
Thursday	**0.379**	**0.346**	**0.377**	Thursday	**0.372**	**0.342**	**0.372**
	(6.85)	(5.65)	(6.38)		(6.73)	(5.57)	(6.28)
Friday	**0.135**	0.102	0.134	Friday	0.123	0.093	0.124
	(1.95)	(1.37)	(1.74)		(1.77)	(1.24)	(1.61)

Notes: The table reports the estimated coefficients and their Newey and West (1987) robust *t* statistics shown in parentheses for equation (3.5), using equations (3.11) and (3.12) as alternative specifications for the intraday volatility pattern. Returns are calculated from five-minute logarithmic average bid-ask quotes from 2nd January 2002 to 31st July 2003. Quotes from Friday 21:05 to Sunday 21:00 are excluded giving 118, 656 observations. The absolute value of de-meaned five-minute returns is standardised by a daily volatility factor obtained from a MA(1)-FIGARCH(1,d,1) model fitted to a longer daily sample of spot exchange rates from 2nd January 1999 to 31st July 2003 as specified by equations (3.8) and (3.9). Bold denotes significant coefficients at a minimum 5% level of significance.

Finally, as described more fully in section 3.4, the model controls for the average impact of all US macroeconomic news combined.[36] The parameter estimate for the 'US News' coefficient measures the extent to which the absolute returns load onto the predetermined volatility pattern following an announcement of US news.

Consistent with the time series dependencies evidenced in section 3.3.8, $\hat{\sigma}_{t,n,FI}$ is selected as the preferred measure of the daily volatility factor and the corresponding estimation results for the full model, which involves controlling for calendar and US macroeconomic announcements, are presented in Table 3.5.1.1. Whilst coefficient estimates and their associated robust *t* statistics are reported for the FFF and cubic spline intraday volatility pattern in Panel (A), there is very little economic interpretation to be gained from these parameters, which are therefore not discussed further. Rather, the relative success of the intraday volatility model is to be judged by comparing the fitted pattern to the corresponding sample average patterns and assessing the time series properties of filtered absolute returns.

To demonstrate the estimation results more effectively, Figures 3.5.1.1 and 3.5.1.2 show the fitted intraday volatility pattern for each currency, separated by winter time and DST, for the FFF and cubic spline intraday models.[37] Rather than plot each pattern for each weekday, day of the week dummies are removed from the regression to generate an average pattern, with the 'Monday Early' effect illustrated by the dotted line to the left of the plots and the 'Friday Late' effect shown by the dashed line at the right. Figure 3.5.1.1 shows the smooth cyclical nature of the FFF pattern which clearly captures the rise in volatility when Sydney, Wellington and Tokyo traders are active, then a decline through the afternoon in Tokyo before rising again as European traders begin their day. The slowdown in volatility in the morning in the UK and Europe is also shown, along with the increase to a peak when UK and US trading activity overlaps and then a steady decline through the US afternoon. Although not statistically significant, the plots show a slowdown in volatility on Monday morning for EUR-USD and EUR-JPY and on Friday night for EUR-USD.

[36] From the evidence in section 3.3.7, US news appears to be the only source of volatility and dominates the impact of news from other countries and so the modelling procedure controls for these important announcements only. A full examination of each individual release is presented in section 3.5.3.

[37] The fitted patterns are based on the estimation of equation (3.5) using equations (3.11) and (3.12) as alternative specifications for the intraday volatility pattern and using $\hat{\sigma}_{t,n,FI}$ as the daily volatility factor.

Figure 3.5.1.1. Fitted Intraday Log-Volatility Patterns for FFF Model.

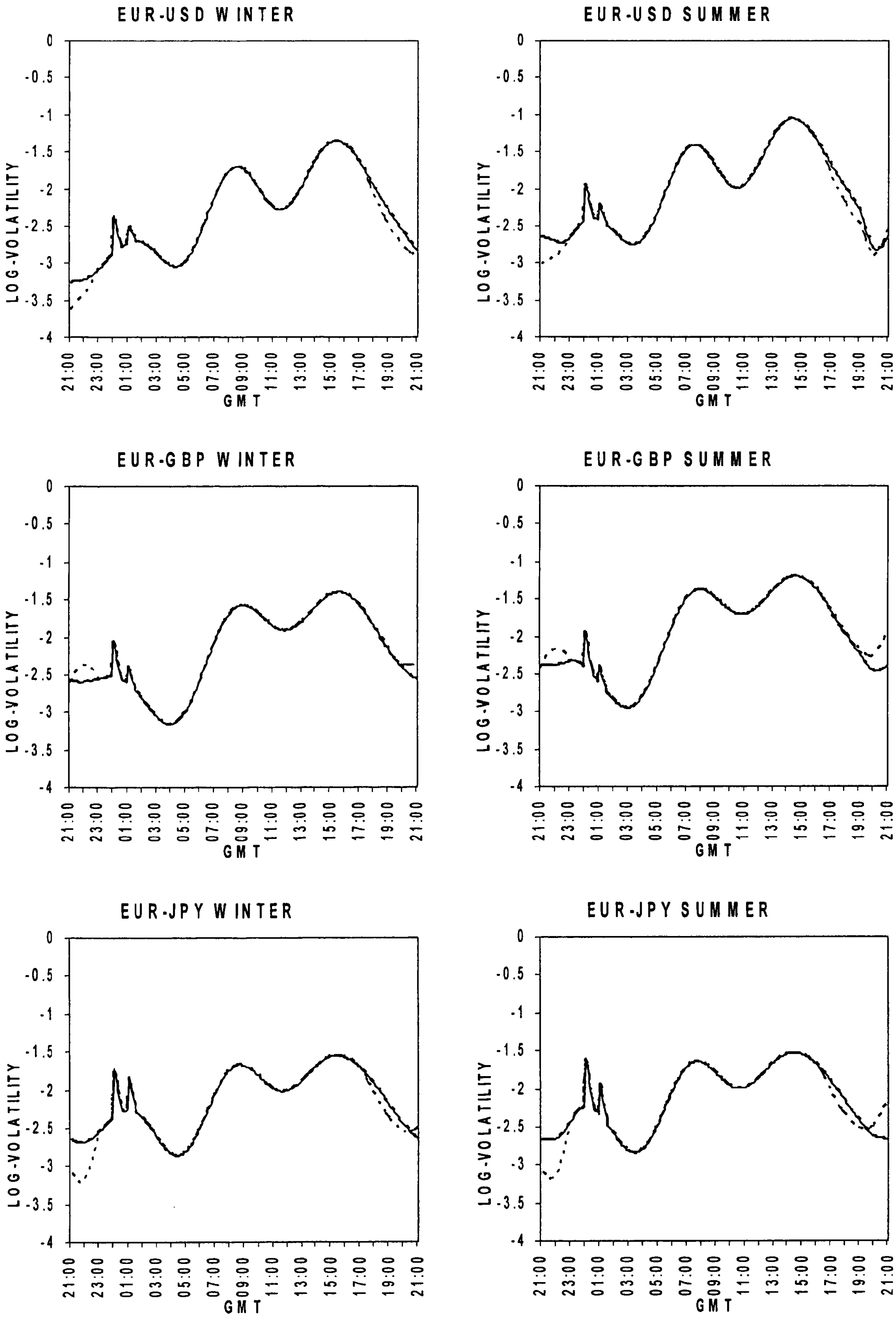
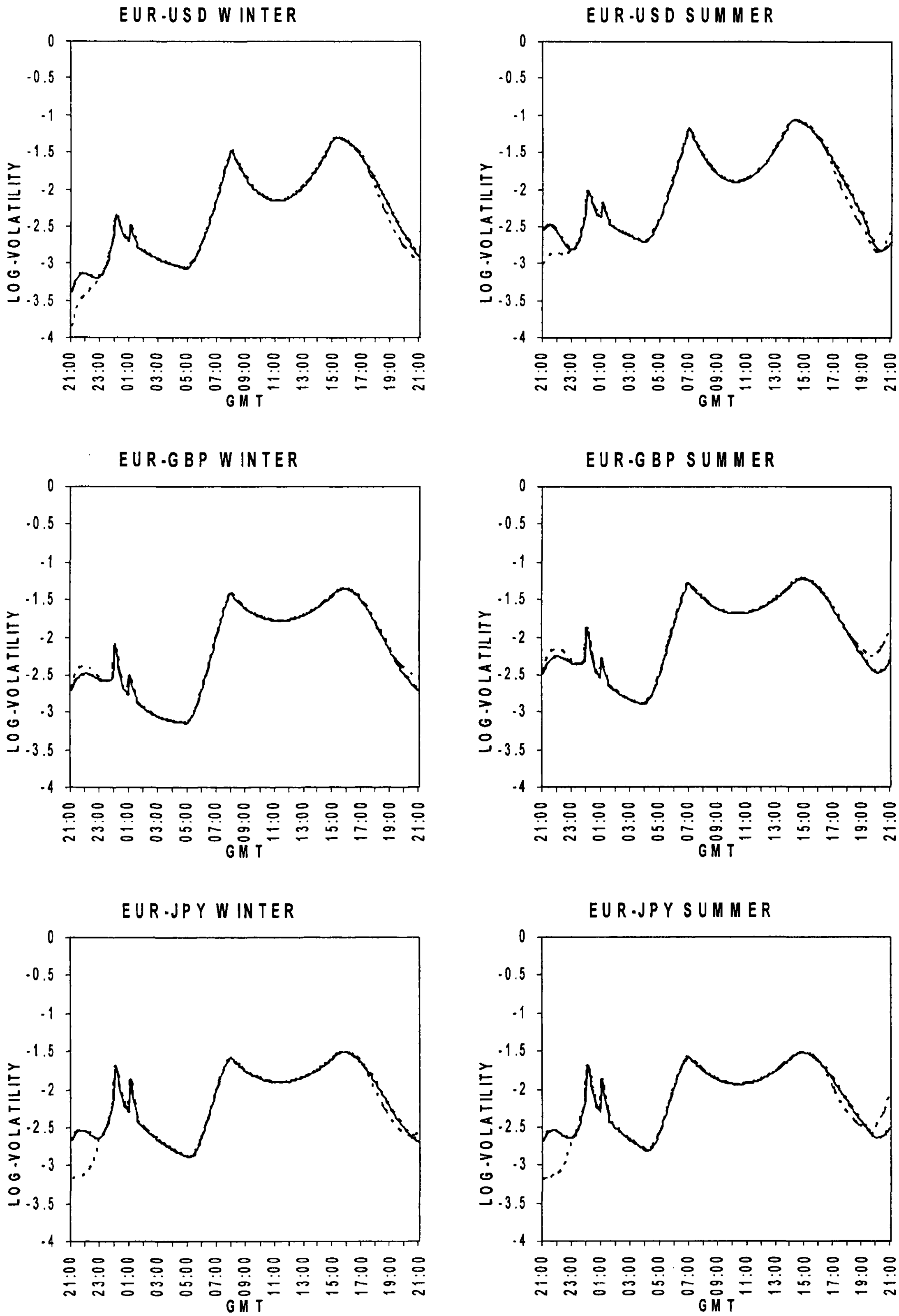


Figure 3.5.1.2. Fitted Intraday Log-Volatility Patterns for Cubic Spline Model.



The Tokyo market opening effect at 00:00 GMT and the effect of the opening of markets in Hong Kong, Singapore and Malaysia one hour later are also clearly shown, being particularly pronounced for EUR-JPY. The corresponding patterns for the cubic spline intraday models are shown in Figure 3.5.1.2. In general, the patterns are very similar. In addition to the flexibility of the positioning of the knots, an advantage of the cubic splines over FFF is that it does not impose a smooth pattern on intraday volatility, but allows sharp peaks and troughs. A clear example is the peak during morning trading in Europe and the UK. Although the sharpness of this peak does not diverge greatly from the FFF pattern, this feature may be of more critical importance if the position of the knot at this peak coincides with a macroeconomic news announcement.

Superimposing the sample average log volatility patterns onto the fitted patterns in Figures 3.5.1.3 and 3.5.1.4 reveals the success of the models in capturing the intraday volatility dynamics. The fit is particularly good for EUR-USD and EUR-JPY and for both winter time and DST, whilst the actual EUR-GBP patterns show much wider dispersion around the fitted pattern. Both the FFF and cubic spline functions show accurate fits, however, the cubic spline patterns appear to fit marginally better at the knot positions. As previously mentioned, this may have important implications for the volatility response patterns for macroeconomic news announcements coinciding with these knots.

Another important gauge of the success of the models is the corresponding fit in the absolute return dimension. To convert the logarithmic fitted pattern to absolute returns, equations (3.3) to (3.12) imply

$$\left|R_{t,n} - \overline{R}\right| = N^{-1/2} \cdot \hat{\sigma}_t \cdot \exp[E(\log s_{t,n})/2] \cdot \exp(\hat{u}_{t,n}/2). \qquad (3.17)$$

From the estimation of equation (3.5), an unconditional, one day ahead intraday forecast is generated by using $\overline{\sigma}_{FI}$ in place of $\hat{\sigma}_{t,FI}$, evaluating E(log$s_{t,n}$) using the estimated coefficient values and averaging $\exp(\hat{u}_{t,n}/2)$ over the relevant residuals in the sample.[38]

[38] This procedure ignores potential correlation between $\hat{\sigma}_{t,n}$ and the transformed error term. See Andersen and Bollerslev (1998a) for details.

Figure 3.5.1.3. Actual and Fitted Intraday Log-Volatility Patterns for FFF Model.

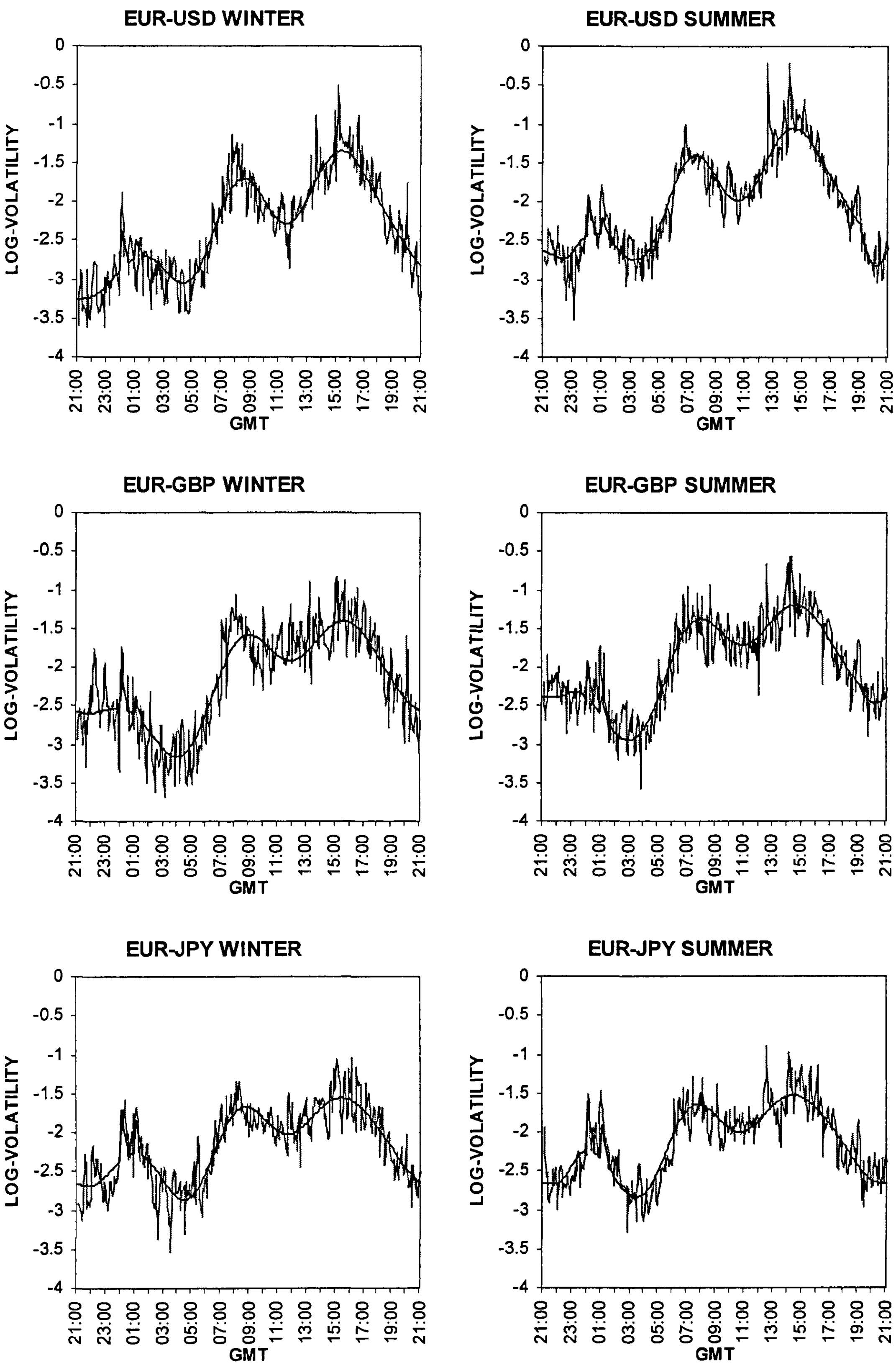
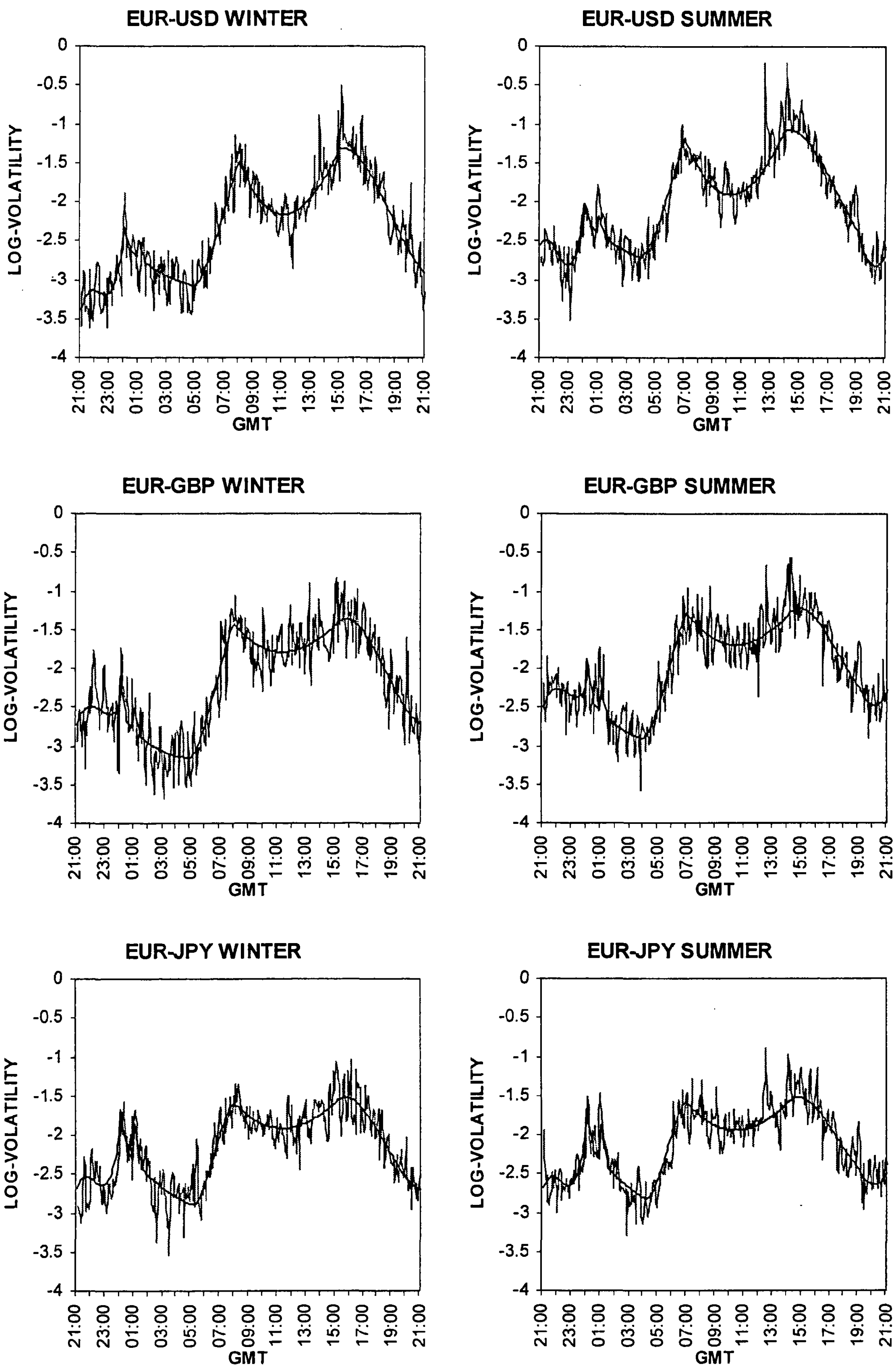


Figure 3.5.1.4. Actual and Fitted Intraday Log-Volatility Patterns for Spline Model.



The unconditional patterns are contrasted to the actual average absolute returns in Figures 3.5.1.5 and 3.5.1.6. In confirmation of previous results, the fit in the absolute return dimension is excellent for EUR-USD and EUR-JPY. For EUR-GBP, the intraday pattern is accurate, but the fit is not as good as for the other two currencies. This is somewhat perplexing given the excellent fit displayed by EUR-GBP in the log-volatility dimension. Again, the intraday fits are similar between the FFF and cubic splines, although the cubic splines show slightly more precision around the knot positions.

In addition to the satisfactory intraday fit of the modelling procedure, the success of the FFF and cubic spline approaches in filtering out the intraday market microstructure effects ultimately depends on their time series performance, and in particular, their ability to account for the repetitive pattern of the autocorrelations displayed in Figures 3.3.8.1 to 3.3.8.3. To test this performance, Figures 3.5.1.7 to 3.5.1.9 show the 10-day autocorrelation functions (ACF) for the five-minute raw, absolute de-meaned returns, $|R_{t,n} - \overline{R}|$ (dotted line), and the five-minute, filtered absolute de-meaned returns $|R_{t,n} - \overline{R}| / \hat{s}_{t,n}$ (solid line), where $\hat{s}_{t,n}$ denotes the normalised estimate for the periodic component from the FFF and cubic spline regressions. Specifically, if $\hat{x}_{t,n}$ denotes the estimated value of the right hand side of equation (3.5),

$$\hat{s}_{t,n} = \frac{TN \cdot \exp(\hat{x}_{t,n} / 2)}{\sum_{t=1}^{T} \sum_{n=1}^{N} \exp(\hat{x}_{t,n} / 2)}, \tag{3.18}$$

such that the normalisation implies $\sum_{t=1}^{T} \sum_{n=1}^{N} \hat{s}_{t,n} \equiv 1$.

Figure 3.5.1.7 shows that the ACF's for raw absolute EUR-USD returns exhibit a striking repetitive pattern with the slowly declining U shape pattern occupying exactly one day intervals. The filtered series, however, show a positive and slowly declining ACF that is largely free of any daily periodicity. Both the FFF and cubic spline specifications, therefore, perform admirably in filtering the intraday EUR-USD volatility.

Figure 3.5.1.5. Actual and Fitted Intraday Volatility Patterns for FFF Model.

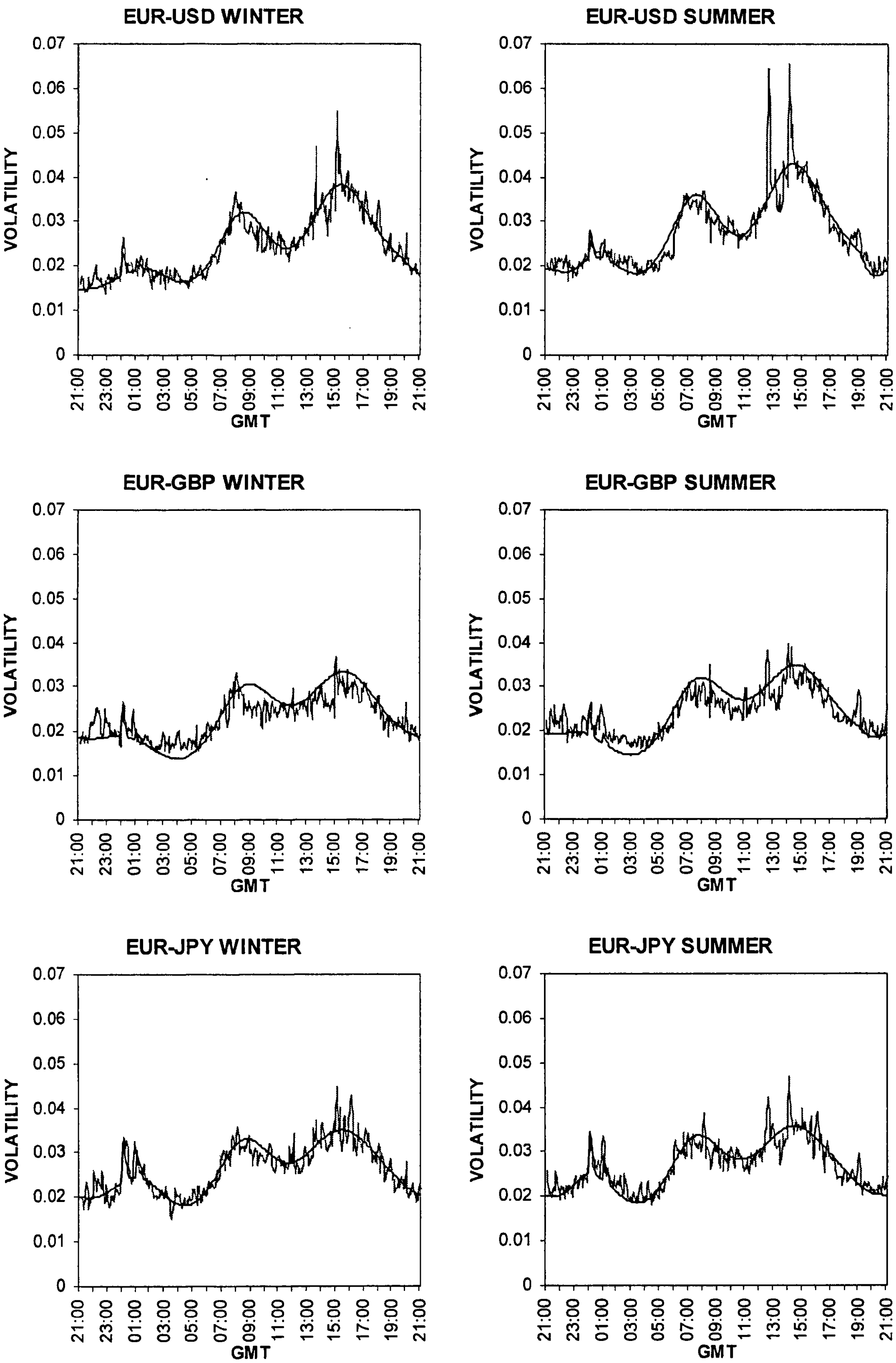


Figure 3.5.1.6. Actual and Fitted Intraday Volatility Patterns for Cubic Spline Model.

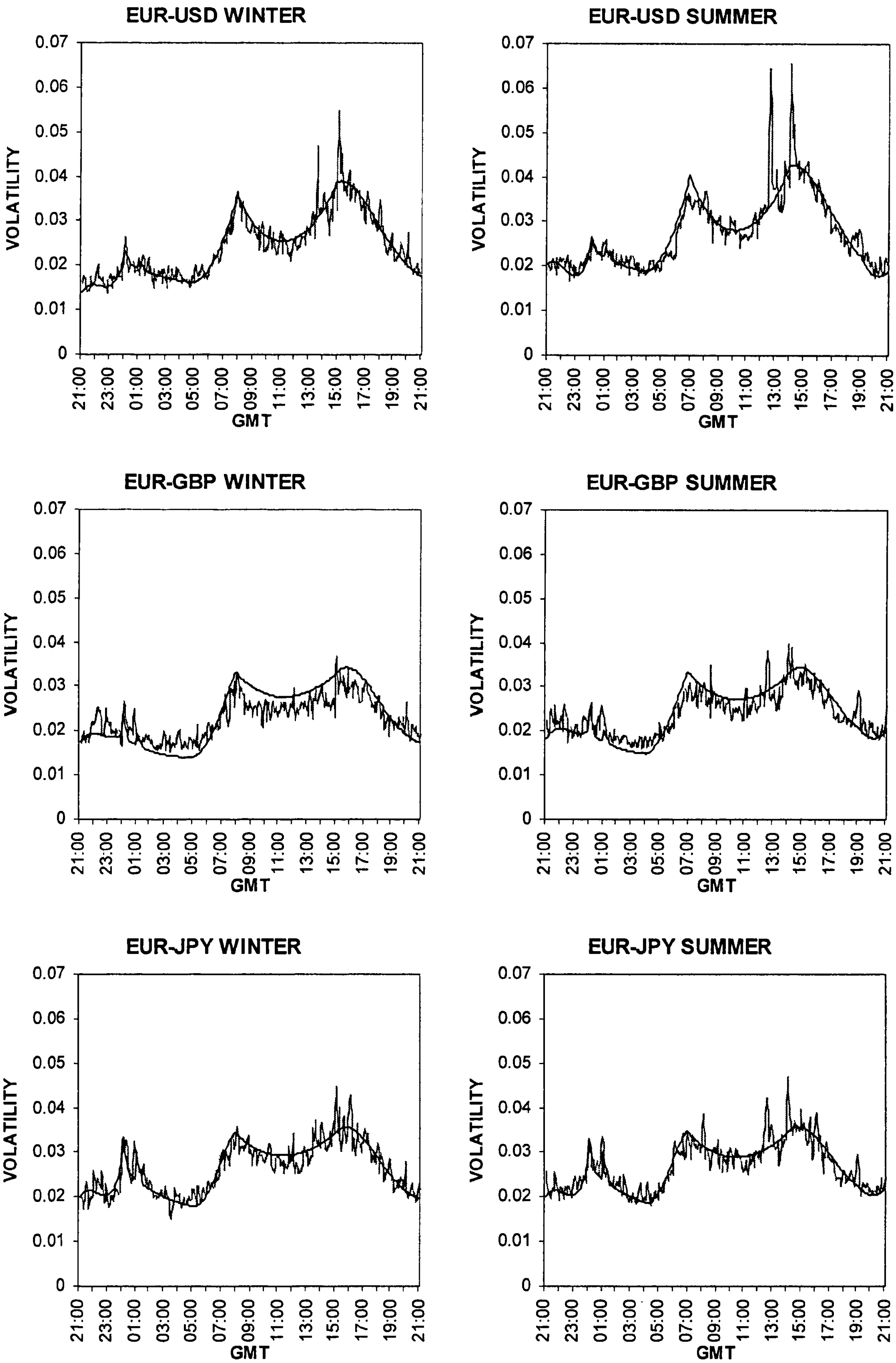


Figure 3.5.1.7. 10 Day ACF for Raw and Filtered EUR-USD Absolute Returns.

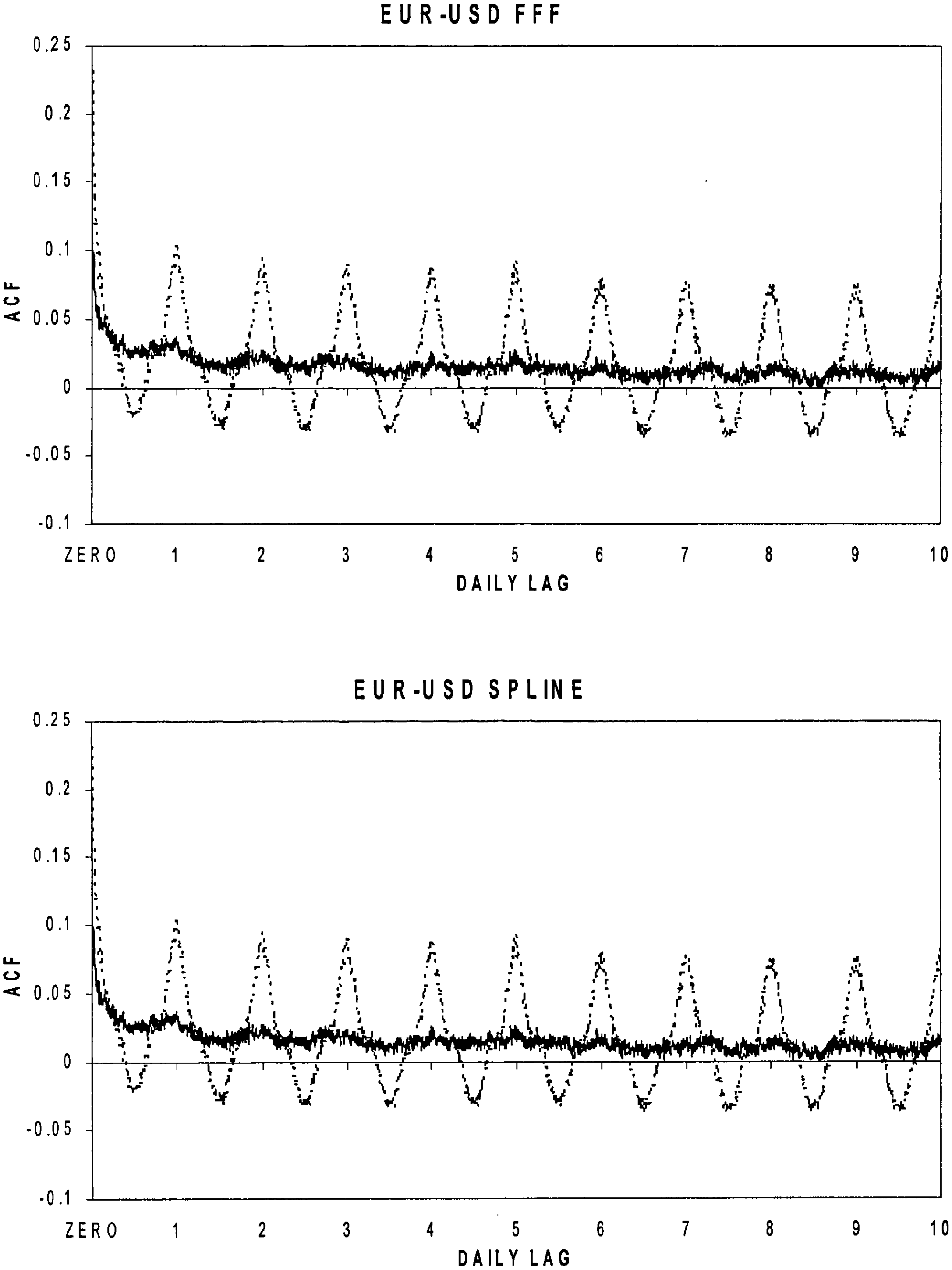
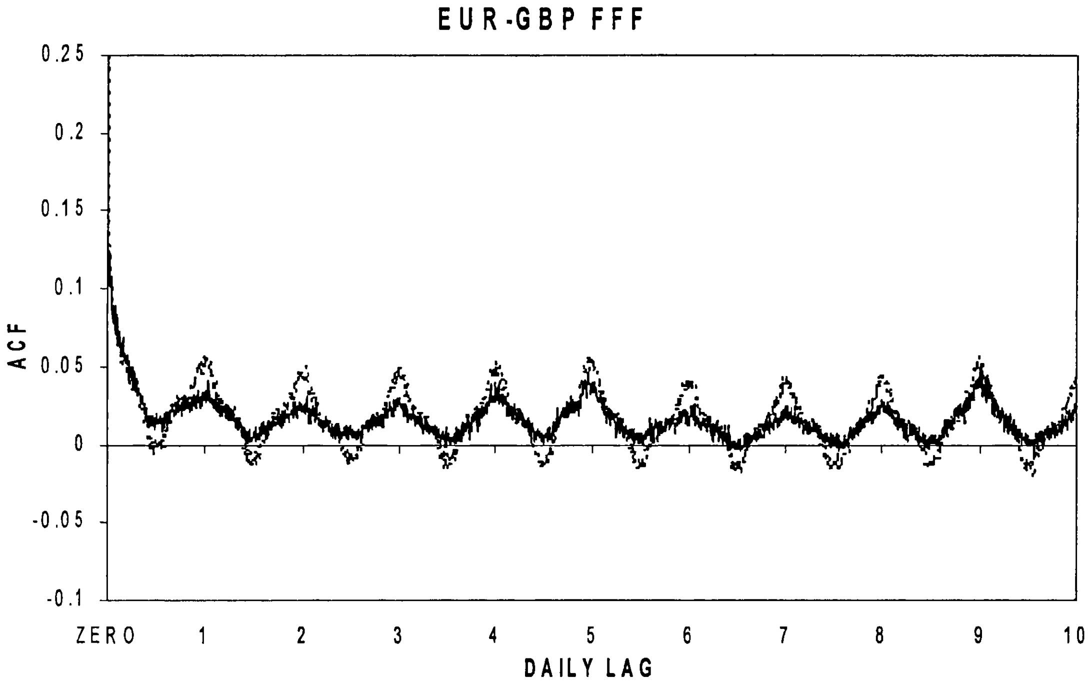


Figure 3.5.1.8. 10 Day ACF for Raw and Filtered EUR-GBP Absolute Returns.



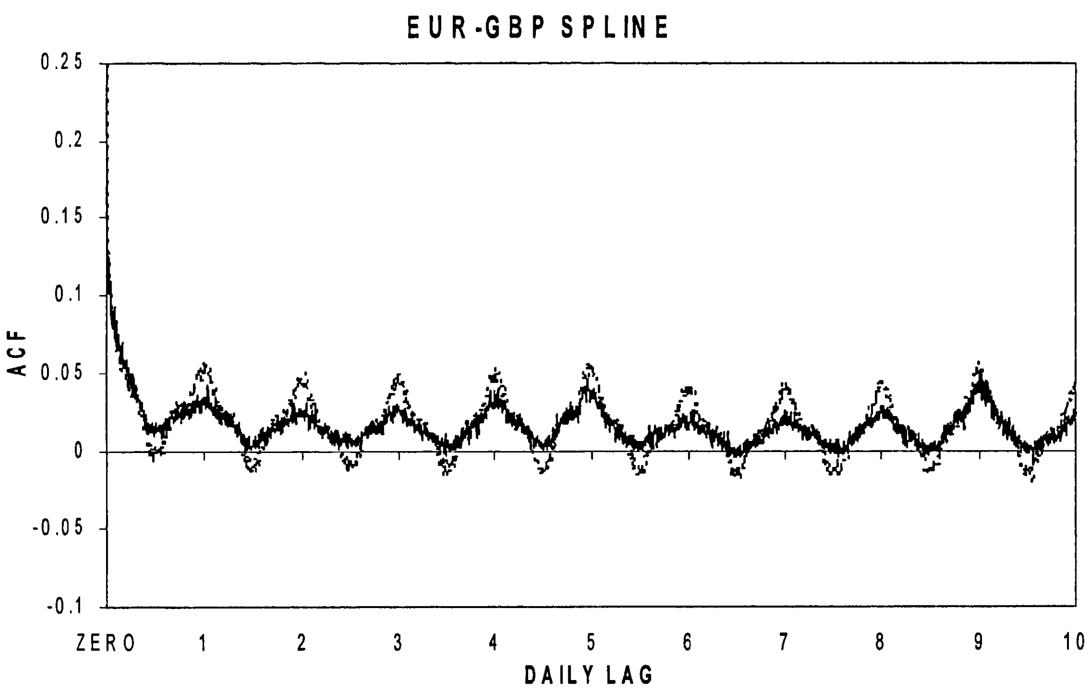
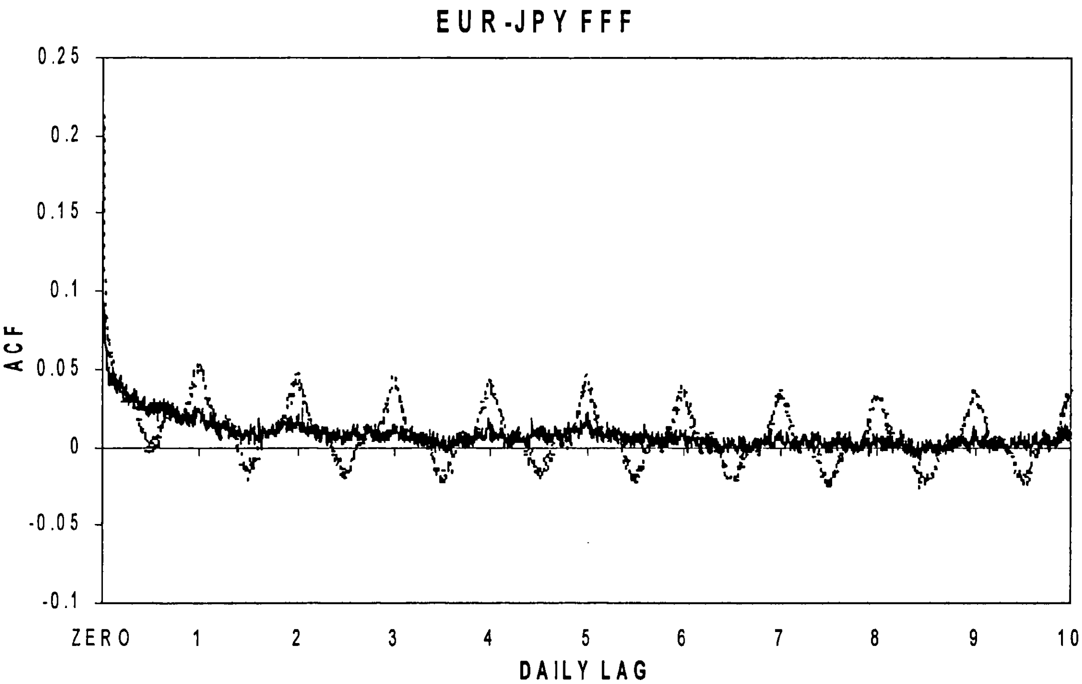
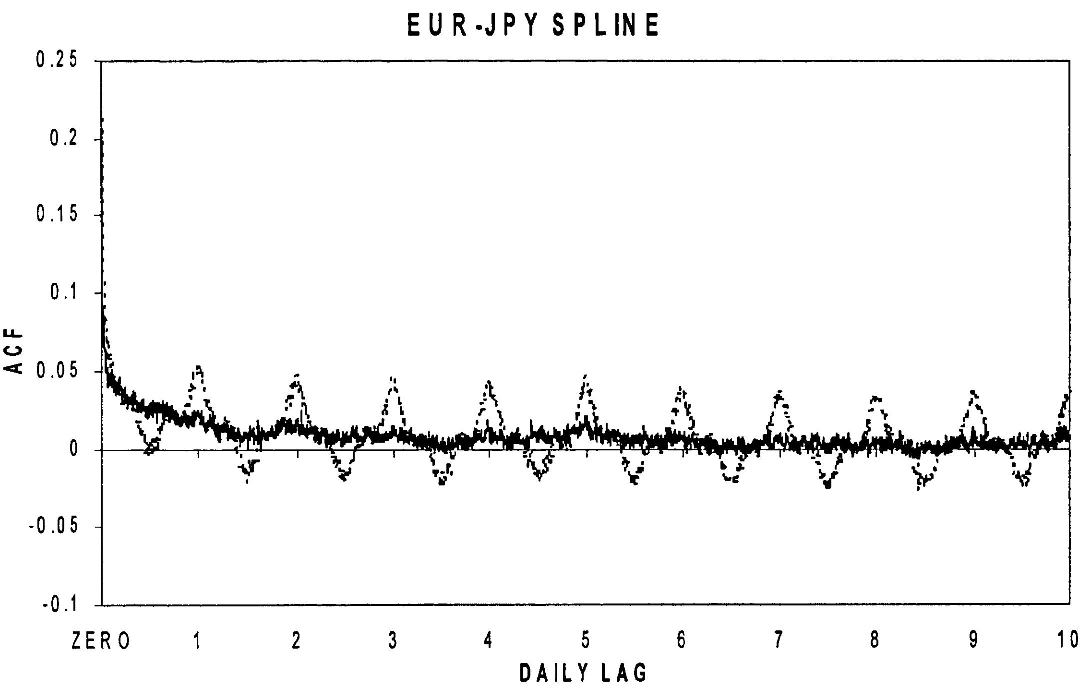


Figure 3.5.1.9. 10 Day ACF for Raw and Filtered EUR-JPY Absolute Returns.





Once this intraday periodicity is annihilated, the rapid initial decay in the ACF followed by an extremely slow rate of decay thereafter is more clearly identified, the long memory dependencies standing out as an inherent feature of high frequency returns. There is very little difference between the FFF and cubic spline filters demonstrating that they both perform very well in capturing the intraday periodicity in the absolute returns.

For EUR-GBP, the intraday filters do not perform as well; periodic dependencies have been reduced, but not entirely eliminated, the remaining periodicity in the filtered series displaying a symptom of the relatively worse fit to the intraday average absolute returns shown in Figures 3.5.1.5 and 3.5.1.6. Nevertheless, the ACF is very small in magnitude, and abstracting from the remaining periodicity, it again shows a rapid initial decline and then a slower rate of decay thereafter. Periodicity in the ACF is almost entirely eliminated for EUR-JPY by both the FFF and cubic spline filters, shown by the plots in Figure 3.5.1.9. The long memory dependency again stands out as a striking feature inherent in the returns process, which is emphasised once the daily periodicity is filtered away.

3.5.2 Calendar Effects

Panel (B) of Table 3.5.1.1 reports the $\hat{\lambda}_k$ coefficient estimates and their associated robust t statistics for all calendar and macroeconomic announcement effects. There is a strong market opening effect in Tokyo for all three currencies and the effect appears to be stronger under the FFF specification. This is entirely expected since the flexibility of the cubic spline formulation allows the positioning of a knot at 00:00 GMT, precisely the same time as the onset of this calendar event, allowing some of the Tokyo market opening effect to be captured by the intraday pattern. The FFF pattern is more cyclical in design and so a more aggressive jump in volatility away from this pattern is to be expected at Tokyo market opening. The effect is also stronger for EUR-JPY, the opening of markets in Tokyo causing higher volatility for JPY. There is also a noticeable increase in volatility, and for EUR-JPY in particular, caused by the simultaneous opening of markets in Hong Kong, Singapore and Malaysia. Since there is no knot positioned at 1:00 GMT in the cubic spline pattern, the coefficient estimates for this effect are very similar for both intraday model specifications.

EUR-USD volatility decreases considerably during regional holidays, as expected, and this effect is also apparent for EUR-GBP and EUR-JPY although it is not statistically significant in these latter cases. The coefficient on the control for all US macroeconomic news announcements combined is equal to one, which is entirely as expected since it is this specification of the model that was used to calibrate the dynamic volatility patterns in response to news events. The high degree of statistical significance observed for this coefficient is particularly noteworthy for all three exchange rates. In contrast, Monday morning and Friday evening slowdowns are not significantly different from zero for any currency. There is clear evidence of a slowdown in EUR-USD volatility in the early part of days during winter time, as suggested by the graphical evidence in section 3.3. The shift in timing regimes from winter to DST causes a leftward shift in the intraday pattern by one hour, but this generates a significant slowdown in volatility at the end of the day for EUR-USD only and is specific to the FFF intraday pattern. Volatility is systematically higher during DST and statistically significantly so in five of the six models estimated. Finally, when controlling for all calendar effects and the impact of US news announcements, there is a strong day of the week effect with Tuesdays and Thursdays showing particularly high volatility relative to the other weekdays. Controlling for the average impact of US news does not eliminate this weekly effect, suggesting that other microstructure features specific to the foreign exchange market are driving it.[39]

Finally, it is important to consider the economic significance of the estimated coefficients relating to the calendar effects in Panel (B) of Table 3.5.1.1. The $\hat{\lambda}_k$

---

[39] The results in Table A.1.1 of Appendix 1 present the estimated coefficients and their associated robust t statistics from a different version of the model. Absolute de-meaned returns are standardised by $\hat{\sigma}_{t,n,\overline{FI}}$, which uses the sample mean of $\hat{\sigma}_{t,n,FI}$ and thus ignores any temporal variation in this volatility factor. Whilst this version of the model does nothing to alleviate heteroscedasticity at the daily frequency, it ensures that there is no practical, generated regressors problem, which may exist when using $\hat{\sigma}_{t,n,FI}$. As Table A.1.1 confirms, the parameter estimates are largely unchanged and the qualitative features of the inference unaffected, so the inclusion of $\hat{\sigma}_{t,n,FI}$ does not, therefore, seem to give rise to a generated regressors problem. As a robustness check, Table A.1.2 reports the estimation results for the version of the model that uses $\hat{\sigma}_{t,n,G}$ as the daily volatility factor, generated from an orthodox MA(1)-GARCH(1,1) model rather than its fractionally integrated counterpart. Again, parameter estimates and inferences are similar to those presented in Table 3.5.1 showing that the intraday pattern, calendar features and macroeconomic effects are not influenced by the choice of the daily volatility measure. The robustness is confirmed by Table A.1.3 which reports the estimation output from the model using $\hat{\sigma}_{t,n,\overline{G}}$ as the constant daily volatility factor. As expected, other than the constant, these results are identical to those of Table A.1.1.

estimators associated with the simple dummy variables measure an incremental, multiplicative factor to volatility. A coefficient of unity signifies a multiplicative factor of exp(1/2)≈1.65, thus volatility increases by an incremental 65 percent in the corresponding interval. For the FFF intraday volatility model, EUR-USD volatility for intervals during regional holidays is 12.1% lower than usual, with the effect applied uniformly to each interval covered by the holiday dummy. There is an incremental increase in volatility per interval of 10.6% during DST, 19.1% on Tuesdays, 8.6% on Wednesdays, 20.9% on Thursdays and 7.0% on Fridays. The corresponding figures for EUR-GBP and EUR-JPY are much smaller and all of these effects are confirmed by the estimates obtained form the cubic spline intraday volatility model.

Interpretation of the other calendar effects is more complex because the regressors are not simple dummy variables, but involve dynamic response patterns governed by polynomial structures expressed in equations (3.13) or (3.14). The instantaneous jump in volatility is then calculated as $\exp(p(0)/2)-1$, the response at the τth lag equals $\exp(p(\tau)/2)-1$ and the cumulative response over the response horizon is given by $\sum_{\tau=0}^{\Omega}[\exp(p(\tau)/2)-1]$. The Tokyo market opening, for example, shows an instantaneous jump measure of 0.287 and a cumulative response measure of 0.97, which imply that volatility jumps by 28.7% in the interval immediately following the opening of markets in Tokyo and that a proportion of 0.97 of the average absolute return during this period is added over the event's response horizon. Since volatility is low at this time of day at 0.02%, the full impact over the event horizon amounts to an additional 0.0194%. The median daily cumulative absolute return for EUR-USD over the sample is 7.42%, so the Tokyo opening effect constitutes only 0.26% of the return variability over a typical trading day. Therefore, although the effect is statistically significant and pronounced, it is of limited economic importance. The effect on EUR-GBP is even smaller, whilst the corresponding estimates for EUR-JPY show an instantaneous jump in volatility of 37.2%, but a cumulative response of only 0.33% of the median daily cumulative absolute return (7.55% for EUR-JPY). Coefficient estimates are much smaller when using the cubic spline version of the intraday volatility because of the position of a knot at Tokyo market opening, but this calendar effect is no more significant in economic terms under the different specification. The opening of markets in other East Asian centres also produces lower coefficient estimates for all three currencies than the Tokyo market opening effect, showing that this event contributes an even smaller proportion to daily return variability. Even the largest coefficient associated with the 'Hong Kong' effect, shown for the cubic spline version for EUR-JPY, explains only 0.23% of the daily EUR-JPY returns variability.

The analysis of all the other calendar effects reveals a similar conclusion. Early Monday mornings contribute, at most, a reduction in volatility of 0.64% of the daily cumulative absolute returns. During winter time, the reduction in volatility on Friday night is a proportion of 1.16% of daily volatility, whilst the corresponding figure for DST is 1.78% with the effect lasting an hour longer. For completeness, the early volatility slowdown during winter time for EUR-USD and the summer slowdown explain only 0.62% and 0.84% of the median daily cumulative absolute returns. Therefore, although these calendar effects present interesting deviations from the intraday volatility pattern, in many cases they are only marginally statistically significant and are insignificant in economic terms, as judged by their effect on volatility over the entire horizon of the response and against cumulative absolute returns over a typical day.

3.5.3 Macroeconomic Announcement Effects

For the results presented in Tables 3.5.1.1, the estimated models control for the average impact of US macroeconomic news, which is isolated as the most important news based on the graphical evidence of section 3.3, and section 3.3.7 in particular, and regressions on simple dummies, the results of which are shown in Table 3.4.1. Allowing a one hour response horizon for all news, except monetary policy announcements by the FOMC and the Employment Report which are afforded a two hour response window, the volatility response is approximated by a third order polynomial restricted to reach zero at the end of the response horizon. This pattern is calibrated by combining all US announcements to determine the estimates of the polynomial coefficients. The subsequent pattern based on these estimates represents the fixed volatility response pattern such that the $\hat{\lambda}_k$ estimates measure the degree to which an announcement loads onto this pattern. In order to assess the importance of each individual announcement, US news is controlled for throughout while estimating the marginal impact of the release under investigation. To analyse individual US news releases, the announcement in question is removed from the control group. Tables 3.5.3.1 to 3.5.3.6 show the coefficient estimates, robust t statistics, the percentage instantaneous jump in volatility, and the cumulative effect on volatility over the response horizon as a percentage of the median daily cumulative absolute returns for all significant announcements.[40] Announcements are ordered by their contribution to daily returns variability. Consistent with the analysis of calendar effects in the previous section, the instantaneous jump in volatility is measured by $\exp(\hat{\lambda}_k \cdot p(0)/2)-1$, the volatility response at the τth lag is calculated as $\exp(\hat{\lambda}_k \cdot p(\tau)/2)-1$ and the cumulative response over the event horizon equals $\sum_{\tau=0}^{\Omega}[\exp(\hat{\lambda}_k \cdot p(\tau)/2)-1]$, where $p(\tau)$ is the predetermined volatility response pattern.[41]

Tables 3.5.3.1 and 3.5.3.2 clearly show the dominance of US news in impacting EUR-USD volatility; of the first twenty announcements in each table, sixteen are from the US. Interest rate decisions announced by the FOMC are by far the most important announcement, causing the largest instantaneous jump in volatility measuring 815% and 835% for the FFF and cubic spline patterns, respectively, with the associated cumulative responses calculated as 12.79% and 13.75% of daily volatility. The sample has been selected specifically to include a period when monetary policy authorities were lowering interest rates and when interest rate announcements were surrounded by great uncertainty, making the timing of decisions to cut interest rates and the magnitude of the cuts very difficult to predict, particularly for the FOMC and European Central Bank (ECB). This is the first study of this kind to investigate macroeconomic announcement effects during such a turbulent economic environment. Over the sample, the FOMC reduced interest rates three times: by 50 basis points on 30th January 2002; by 50 basis points on 6th November 2002 and by 25 basis points on June 25th 2003 and this period of aggressive monetary policy relaxation caused dramatic movements in the EUR-USD exchange rate.

[40] Significant announcements are selected as those reporting a loading parameter statistically greater than zero at the 10% level.
[41] Tables A.2.1 to A.2.6 of Appendix 2 show all remaining announcements investigated but which did not offer a significantly positive loading coefficient.

Table 3.5.3.1. Significant Announcement Effects for EUR-USD Using FFF Model.

ANNOUNCEMENT	COUNTRY	COEFF	ROBUST T	% JUMP	% DAILY
FOMC Fed. Funds	US	3.63	5.78	815.43	12.79
Employment Report	US	2.55	7.68	373.14	9.33
GDP Advance	US	2.31	3.11	308.61	4.49
GDP Preliminary	US	1.68	3.18	178.77	2.85
ECB Interest Rate	EU	1.82	4.40	204.30	2.79
Trade Balance	US	1.59	4.97	163.75	2.65
IFO Business Expectations	GER	1.95	5.89	227.90	2.62
Philadelphia Fed. Index	US	1.90	5.59	219.39	2.54
Michigan Sentiment Prelim.	US	1.54	5.45	155.57	2.54
Industrial Production	US	1.52	4.72	153.54	2.51
Chicago PMI	US	1.26	3.06	115.65	1.96
Non-Farm Payrolls Final	FRA	1.51	3.58	151.53	1.86
Consumer Confidence	US	1.16	3.56	102.83	1.77
GDP Provisional	UK	1.38	3.75	132.34	1.66
PPI	US	1.02	3.59	86.60	1.52
Current Account	US	1.02	1.79	85.86	1.51
Michigan Sentiment Final	US	0.96	2.14	79.71	1.41
New Home Sales	US	0.89	3.14	71.76	1.29
Productivity Revised	US	0.82	1.56	64.46	1.17
Durable Goods Orders	US	0.81	1.97	63.78	1.16
Retail Sales	US	0.80	1.72	63.29	1.15
Non-Farm Payrolls Prelim.	FRA	0.99	1.84	83.43	1.10
Halifax House Prices	UK	1.06	3.00	90.68	1.07
Labour Costs Final	EU	1.03	1.80	87.93	0.96
Current Account	FRA	0.88	3.25	71.36	0.96
Retail Sales	GER	0.87	1.87	69.71	0.94
Existing Home Sales	US	0.67	1.81	50.15	0.93
GDP	JAP	1.11	1.99	97.45	0.85
Industrial Production	EU	0.89	2.51	72.19	0.81
Consumer Confidence	JAP	0.71	1.91	54.48	0.75
Initial Claims	US	0.55	2.73	39.48	0.74
Retail Sales	JAP	0.99	2.00	82.87	0.73
Industrial Production	GER	0.68	1.94	51.74	0.72
M3	EU	0.67	1.76	50.34	0.70
M2	JAP	0.94	2.27	77.87	0.69
CPI	US	0.47	1.77	33.04	0.63
Consumer Confidence	UK	0.59	1.88	43.47	0.61
Household Survey	FRA	0.54	1.39	39.08	0.55
Retail Sales	UK	0.53	1.58	38.11	0.54
Trade Final	EU	0.62	1.51	45.79	0.53
Household Consumption	FRA	0.45	1.53	31.41	0.45
PMI	FRA	0.43	1.36	29.89	0.43

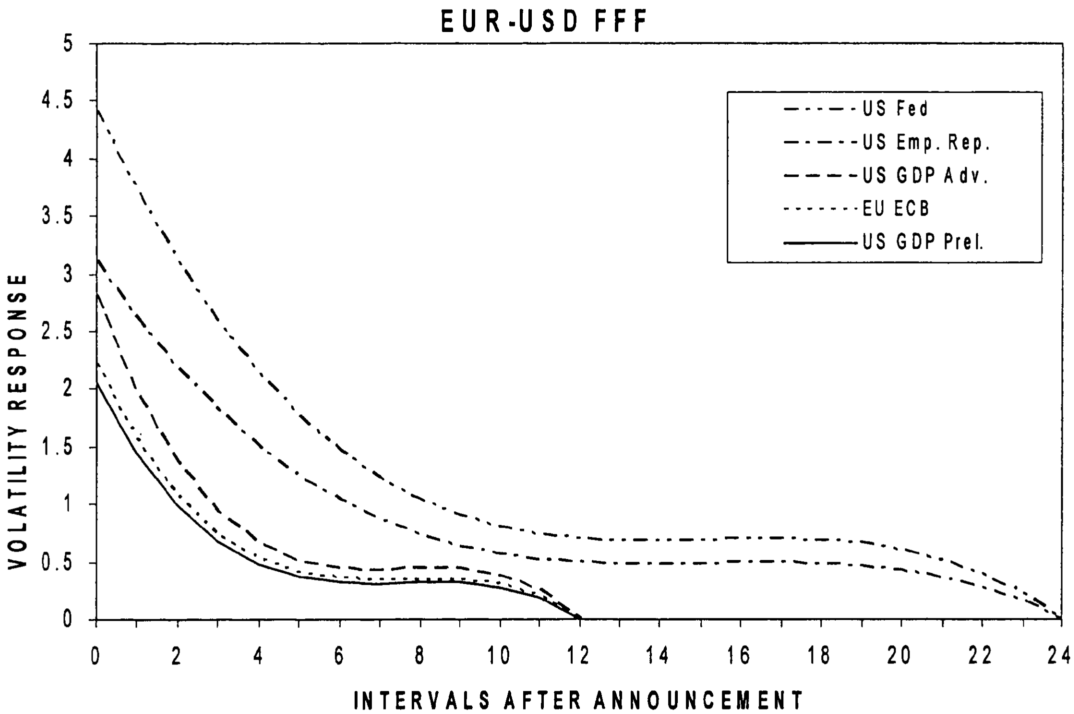
Table 3.5.3.2. Significant Announcement Effects for EUR-USD Using Spline Model.

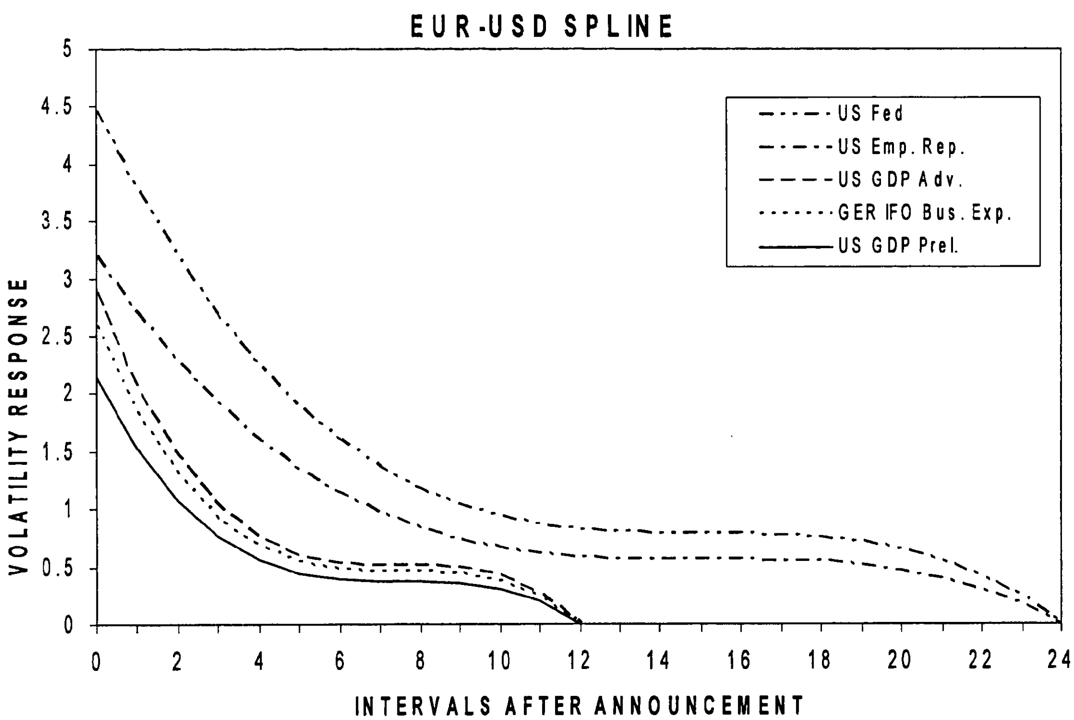
ANNOUNCEMENT	COUNTRY	COEFF	ROBUST T	% JUMP	% DAILY
FOMC Fed. Funds	US	3.58	5.99	834.98	13.75
Employment Report	US	2.55	8.02	392.72	10.28
GDP Advance	US	2.31	3.12	324.02	4.92
GDP Preliminary	US	1.71	3.33	191.32	3.18
IFO Business Expectations	GER	2.08	6.56	266.69	3.14
Trade Balance	US	1.61	5.08	173.67	2.93
ECB Interest Rate	EU	1.77	4.45	201.79	2.91
Industrial Production	US	1.57	4.96	166.70	2.83
Michigan Sentiment Prelim.	US	1.47	5.33	151.36	2.61
Philadelphia Fed. Index	US	1.76	5.29	200.13	2.48
GDP Provisional	UK	1.51	4.15	157.64	2.03
Chicago PMI	US	1.17	2.93	107.96	1.95
Current Account	US	1.06	1.98	94.51	1.73
PPI	US	1.05	3.77	93.17	1.71
Consumer Confidence	US	1.05	3.29	92.49	1.70
Non-Farm Payrolls Final	FRA	1.18	2.95	109.56	1.48
Durable Goods Orders	US	0.91	2.30	76.30	1.43
Michigan Sentiment Final	US	0.89	2.04	73.96	1.39
Productivity Revised	US	0.87	1.79	72.49	1.37
Retail Sales	US	0.87	1.98	71.93	1.36
ISM Non Manufacturing	US	0.84	2.34	68.64	1.30
New Home Sales	US	0.79	2.83	63.39	1.21
M3	EU	0.85	2.30	70.13	1.00
Initial Claims	US	0.65	3.35	50.20	0.98
Halifax House Prices	UK	0.89	2.58	73.86	0.94
Consumer Confidence	JAP	0.77	2.15	61.59	0.89
Existing Home Sales	US	0.58	1.62	44.04	0.87
Labour Costs Final	EU	0.86	1.58	70.96	0.84
Retail Sales	GER	0.73	1.62	57.83	0.84
CPI	US	0.54	2.09	40.04	0.79
Retail Sales	UK	0.69	2.14	54.28	0.79
Unemployment	GER	0.65	1.66	50.10	0.73
GDP	JAP	0.91	1.71	76.62	0.72
Industrial Production	EU	0.73	2.19	58.28	0.70
Housing Completions	US	0.47	1.56	34.27	0.69
PMI	FRA	0.60	1.95	45.54	0.67
Current Account	FRA	0.59	2.18	44.61	0.66
Industrial Production	GER	0.58	1.73	43.98	0.65
Retail Sales	JAP	0.78	1.62	62.41	0.60
M2	JAP	0.75	1.90	60.10	0.58
Consumer Confidence	UK	0.50	1.65	36.52	0.55

Confirming the previous findings of Ederington and Lee (1993), Payne (1996), Andersen and Bollerslev (1998a), Bollerslev et al. (2000) and Andersen, Bollerslev, Diebold and Vega (2003), the Employment Report is also an important indicator, causing immediate jumps in volatility of 373% and 393% for FFF and cubic spline versions, respectively, with the associated cumulative response measures of 9.33% and 10.28% of the median daily cumulative absolute return, respectively. GDP announcements are also crucial with the earlier Advance figures causing a more violent response than the Preliminary data suggesting that traders learn from the Advance indicator and are able to produce more accurate forecasts for the later Preliminary data. In addition to the interesting economic and market microstructure issues that underpin the reaction of volatility to macroeconomic news announcements, the comparison of alternative econometric techniques for capturing the inherent intraday volatility pattern yields important results.

The different specifications for the intraday pattern produce slightly different volatility response patterns that give rise to striking differences in the instantaneous and cumulative response measures. This is exemplified by the fifth entries in Tables 3.5.3.1 and 3.5.3.2 where the next most important news announcement to EUR-USD volatility differs between models. Under the FFF paradigm, interest rate announcements from the ECB contribute the next largest percentage cumulative volatility response calculated as 2.79% with an instantaneous volatility jump of 204% immediately following these announcements. For the cubic spline approach, however, the German IFO Business Expectations survey generates the fifth largest cumulative volatility response measuring 3.14% at the daily level corresponding to an incremental instantaneous volatility response of 267%. The large discrepancy between volatility response measures shows that the characterisation of the volatility response is sensitive to the choice of intraday volatility specification. The discrepancy is sufficiently large in many cases that ordering the announcement effects by their cumulative responses ranks the releases in different sequences of importance. Moreover, whilst allowing response patterns to vary between the intraday models, measures obtained form the FFF approach tend to understate those generated by the cubic spline specification. The estimated volatility response patterns for the top five announcements are illustrated in Figure 3.5.1.1.

Figure 3.5.1.1. Volatility Response Patterns for EUR-USD.





In most instances, the announcements comprising the next 15 entries in Tables 3.5.3.1 and 3.5.1.2 are consistent between both the FFF and cubic spline models, but they are listed in different orders reflecting the different response measures calculated from the alternative intraday models. For 15 of the top 20 announcements in the tables, the FFF model understates the cumulative response as a percentage of daily volatility compared to the cubic spline model. The US Trade Balance features very prominently, confirming the previous findings of Ederington and Lee (1993), Payne (1996), Andersen and Bollerslev (1998a) and Andersen, Bollerslev, Diebold and Vega (2003), but the remaining important US announcements in this top 20 are dominated by forward looking indices such as the Philadelphia Federal Reserve Index, the University of Michigan Sentiment Index (Preliminary and Final) and Chicago PMI. Aside from their economic content and forward looking nature, these indices are released very early and they are typically the first indicators for a particular month that traders will see, so it is perhaps not surprising that they are such important drivers of volatility. Contrary to previous findings that document the importance of more traditional economic announcements such as PPI, Durable Goods Orders, Retail Sales, CPI and Initial Claims for unemployment Benefits, it would seem that the informational content and timing of these forward looking indicators make them a more important source of EUR-USD volatility. The important announcements for EUR-USD volatility emanating from European countries are the ECB monetary policy decision for the Eurozone, German IFO Business Expectations Survey, provisional GDP for the UK and French Non-Farm Payrolls. The general lack of significant Eurozone, German and French announcements, particularly relating to GDP, trade and inflation data, shows that US news generates a more vigorous exchange rate volatility response.

Considering Tables 3.5.1.3 and 3.5.1.4, there is an increased presence and importance of UK news in driving EUR-GBP volatility compared to EUR-USD. US interest rate announcements by the FOMC are again top of the list with instantaneous jumps in volatility of 350% and 362% for the FFF and cubic spline versions, respectively, and cumulative response impacts of 6.89% and 7.38% of the daily level, which are approximately half of the corresponding measures for EUR-USD.

Table 3.5.1.3. Significant Announcement Effects for EUR-GBP Using FFF Model.

ANNOUNCEMENT	COUNTRY	COEFF	ROBUST T	% JUMP	% DAILY
FOMC Fed. Funds	US	4.71	5.15	350.30	6.89
Employment Report	US	3.44	5.30	199.51	6.42
ECB Interest Rate	EU	2.86	3.64	149.01	3.12
GDP Advance	US	2.89	3.14	151.46	2.71
Industrial Production	UK	2.79	5.15	143.84	2.59
Michigan Sentiment Prelim.	US	2.51	4.30	123.02	2.25
Michigan Sentiment Final	US	2.19	2.68	101.39	1.89
GDP Final	UK	2.19	3.50	101.32	1.89
IFO Business Expectations	GER	2.13	3.00	97.19	1.82
GDP Preliminary	EU	2.25	3.39	105.32	1.76
Labour Costs Revised	EU	2.23	2.09	103.99	1.74
Non-Farm Payrolls Prelim.	FRA	2.34	2.65	111.38	1.72
GDP Preliminary	US	1.94	1.43	85.99	1.63
Retail Sales	UK	1.92	2.57	84.86	1.61
MPC Interest Rate	UK	1.85	1.83	80.72	1.54
PPI	GER	2.11	3.94	96.17	1.50
GDP	GER	2.03	1.99	91.35	1.44
Industrial Production	US	1.57	2.08	64.95	1.26
ISM Non Manufacturing	US	1.50	2.07	61.62	1.20
Non-Farm Payrolls Final	FRA	1.65	1.76	69.19	1.11
COL Final	GER	1.64	2.78	68.98	1.11
M3	EU	1.29	2.15	51.08	1.01
Durable Goods Orders	US	1.27	1.53	50.19	0.99
HCPI	EU	1.39	2.37	56.08	0.99
Trade Balance	FRA	1.41	1.65	57.05	0.93
PPI	EU	1.30	1.99	51.32	0.91
CIPS Services	UK	1.08	1.58	41.19	0.82
Industrial Production	FRA	1.25	1.54	48.99	0.81
Unemployment	UK	1.00	1.34	37.65	0.76
Trade Final	EU	1.07	1.68	40.90	0.74
Retail Sales	US	0.83	1.32	30.34	0.62
Import Prices	GER	0.98	1.32	36.63	0.61
BOJ Monetary Policy	JAP	1.16	1.97	45.00	0.60
Consumer Confidence	EU	0.86	1.46	31.41	0.57
Initial Claims	US	0.64	1.82	22.82	0.47

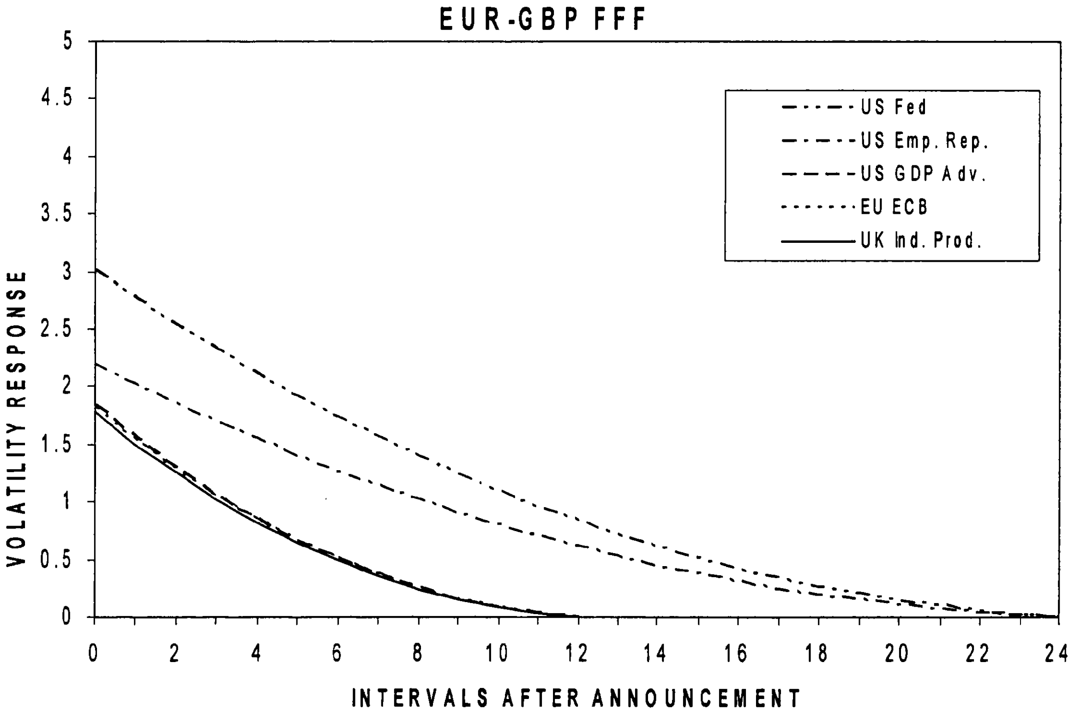
Table 3.5.1.4. Significant Announcement Effects for EUR-GBP Using Spline Model.

ANNOUNCEMENT	COUNTRY	COEFF	ROBUST T	% JUMP	% DAILY
FOMC Fed. Funds	US	4.62	5.28	361.53	7.38
Employment Report	US	3.45	5.63	213.08	7.11
ECB Interest Rate	EU	2.68	3.58	143.17	3.14
Industrial Production	UK	2.93	5.59	163.93	3.04
GDP Advance	US	2.83	3.11	155.46	2.90
Michigan Sentiment Prelim.	US	2.41	4.27	122.42	2.35
GDP Final	UK	2.39	3.86	120.90	2.32
IFO Business Expectations	GER	2.31	3.38	115.06	2.22
Michigan Sentiment Final	US	2.15	2.70	103.58	2.02
Retail Sales	UK	2.10	2.92	100.18	1.96
Labour Costs Revised	EU	2.11	2.07	101.47	1.78
GDP Preliminary	US	1.89	1.43	87.16	1.73
GDP Preliminary	EU	2.04	3.08	96.37	1.70
Industrial Production	US	1.75	2.43	78.51	1.57
Non-Farm Payrolls Prelim.	FRA	1.88	2.20	86.44	1.43
MPC Interest Rate	UK	1.60	1.67	70.08	1.42
PPI	GER	1.77	3.34	79.90	1.33
M3	EU	1.52	2.59	65.19	1.32
BOJ Monetary Policy	JAP	2.05	2.30	97.01	1.27
ISM Non Manufacturing	US	1.46	2.08	62.02	1.26
GDP	GER	1.65	1.65	72.55	1.22
Durable Goods Orders	US	1.34	1.69	56.06	1.15
CIPS Services	UK	1.34	2.06	55.88	1.15
Unemployment	UK	1.27	1.78	52.39	1.08
HCPI	EU	1.26	2.35	52.00	0.97
COL Final	GER	1.34	2.34	56.12	0.96
PPI	EU	1.12	1.79	44.87	0.84
Retail Sales	US	0.90	1.48	34.81	0.74
Trade Final	EU	0.97	1.57	37.72	0.71
Initial Claims	US	0.70	2.01	25.90	0.55
Consumer Confidence	EU	0.73	1.29	27.19	0.52

The Employment Report is again second and shows incremental instantaneous volatility increases of 200% and 213% and cumulative responses of 6.42% and 7.11% of daily volatility for the FFF and cubic spline models, respectively, again more muted reactions than EUR-USD. The ECB interest rate announcements, however, generate a larger proportionate volatility reaction for EUR-GBP than EUR-USD, contributing 3.12% and 3.14% of daily EUR-GBP volatility for FFF and cubic splines, respectively, compared to 2.79% to 2.91% for EUR-USD. UK Industrial Production and the US GDP Advance are the fourth and fifth most important announcements for EUR-GBP volatility, but consistent with Tables 3.5.1.1 and 3.5.1.2, they appear in different places due to the discrepancy between response measures obtained from the two intraday volatility models. Estimated response patterns for these top five announcements are displayed in Figure 3.5.1.2. Final GDP, Retail Sales and MPC interest rate decisions are the other prominent UK releases, whilst Eurozone and German GDP and PPI announcements are also significant and appear in the top 20 releases, showing that UK, Eurozone and German news regarding these more orthodox economic fundamentals are important sources of EUR-GBP volatility. Perhaps the only surprising omission from these top 20 lists is that of Balance of Payments data. Of the top 20 important announcements, 18 are consistent between the two intraday volatility models, but, as in Tables 3.5.1.1 and 3.5.1.2, they are ranked in different orders. The FFF understates the percentage cumulative volatility response compared to the cubic splines in 16 of the 20 announcements, confirming the sensitivity of macroeconomic announcement measures to intraday volatility specifications.

Finally, Tables 3.5.1.5 and 3.5.1.6 show the significant announcements for EUR-JPY with the corresponding estimated response patterns of the top five announcements plotted in Figure 3.5.1.3. Again, US news has a strong influence on EUR-JPY volatility with at least 11 announcements appearing in the top 20 and the releases of forward looking economic surveys causing larger volatility reactions than news about more traditional economic fundamentals. Although FOMC interest rate announcements cause the largest instantaneous jumps in EUR-JPY volatility (309% and 324% for FFF and cubic spline models, respectively), the Employment Report contributes the largest percentage cumulative responses of 4.89% and 5.39% of daily volatility for FFF and cubic spline models, respectively.

Figure 3.5.1.2. Volatility Response Patterns for EUR-GBP.



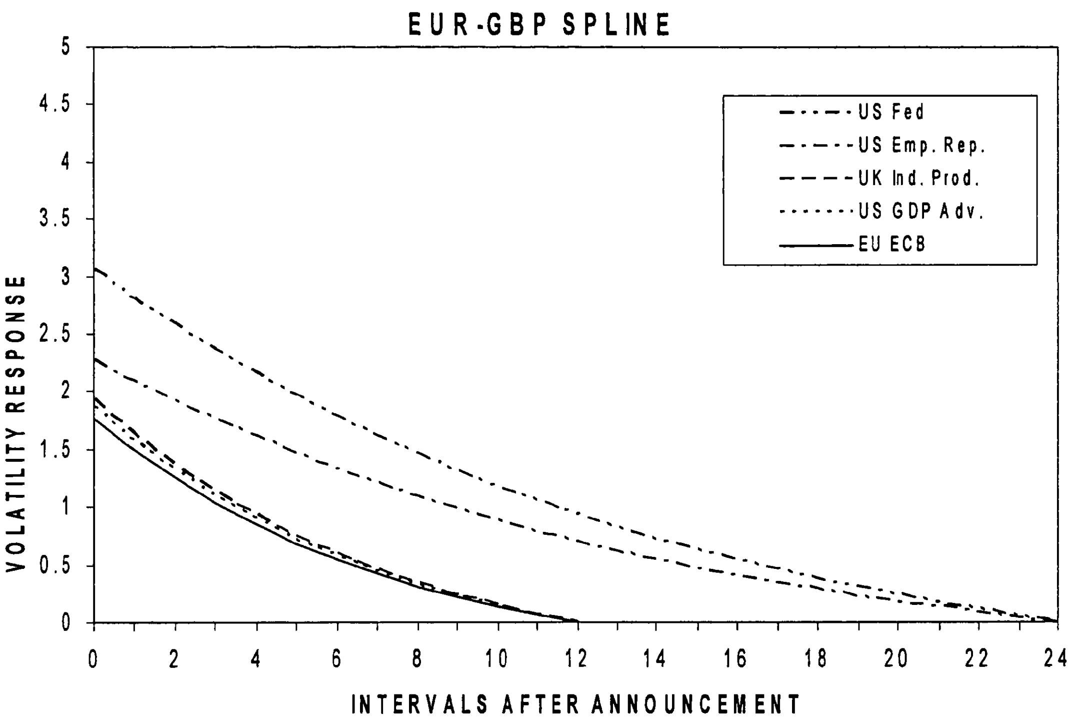


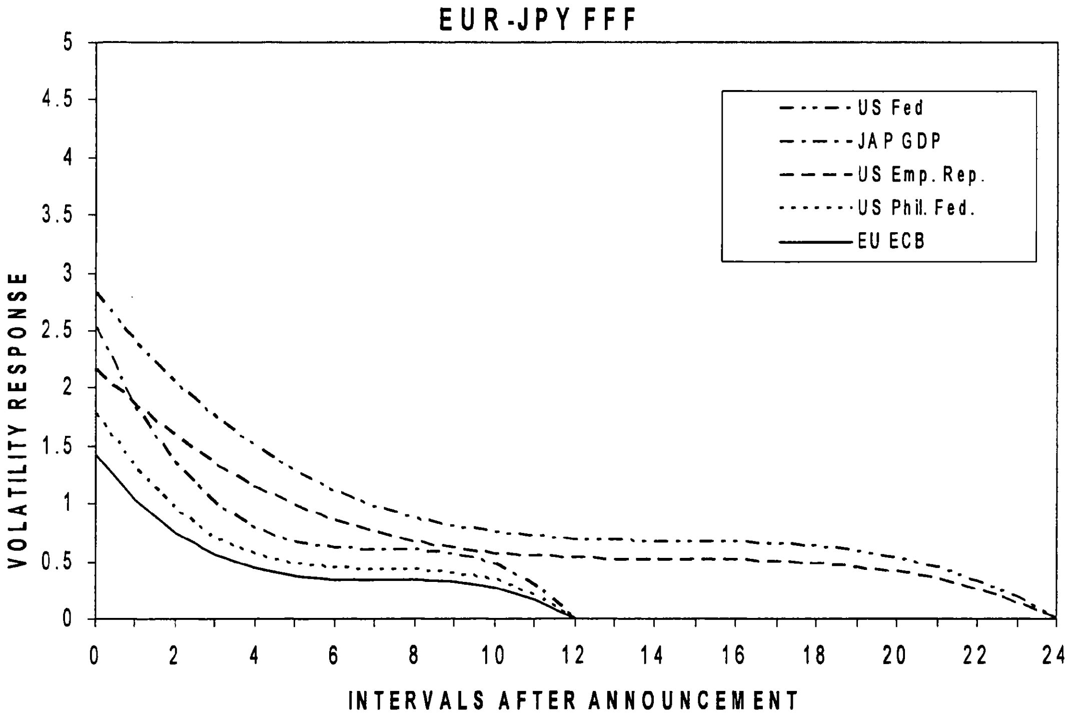
Table 3.5.1.5. Significant Announcement Effects for EUR-JPY Using FFF Model.

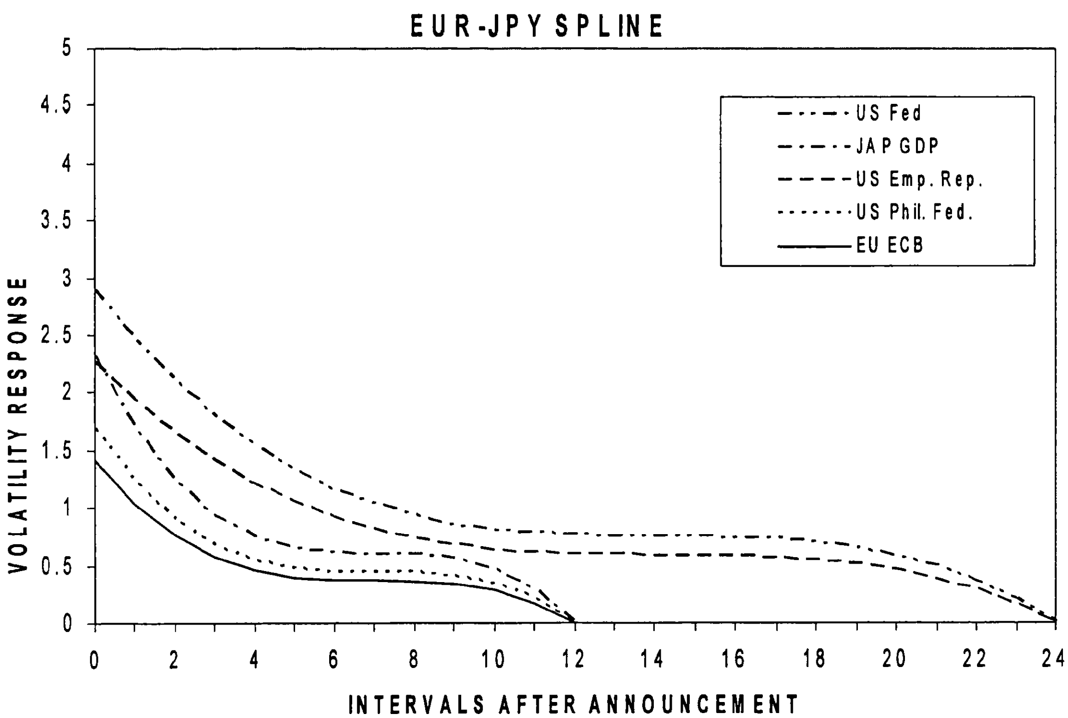
ANNOUNCEMENT	COUNTRY	COEFF	ROBUST T	% JUMP	% DAILY
Employment Report	US	3.10	5.50	195.19	4.89
FOMC Fed. Funds	US	4.03	4.45	309.02	4.71
GDP	JAP	3.63	5.30	255.38	2.21
Philadelphia Fed. Index	US	2.56	5.30	144.84	2.07
ECB Interest Rate	EU	2.04	2.96	104.13	1.81
COL Final	GER	2.46	3.95	136.52	1.64
Michigan Sentiment Final	US	1.96	2.54	98.12	1.48
Durable Goods Orders	US	1.91	3.25	95.05	1.44
GDP Preliminary	US	1.86	2.90	91.67	1.39
Michigan Sentiment Prelim.	US	1.81	3.15	88.39	1.35
Non-Farm Payrolls Final	FRA	2.08	2.67	106.86	1.33
Industrial Production	UK	1.72	2.97	82.58	1.27
GDP Provisional	UK	1.69	1.49	80.30	1.24
Existing Home Sales	US	1.49	2.13	68.18	1.07
Trade Final	EU	1.49	3.73	68.23	1.00
IFO Business Expectations	GER	1.34	1.63	59.85	0.95
Current Account	US	1.34	1.80	59.81	0.95
Trade Balance	US	1.31	1.72	58.37	0.93
HCPI	EU	1.39	1.80	62.66	0.92
New Home Sales	US	1.22	1.52	53.42	0.86
Chicago PMI	US	1.21	1.57	52.88	0.85
Factory Inventories/Orders	US	1.20	1.70	52.39	0.84
BOJ Monetary Policy	JAP	1.71	2.18	81.99	0.84
Industrial Production	EU	1.27	2.38	55.94	0.83
Labour Costs Prelim.	EU	1.26	1.56	55.49	0.83
Consumer Confidence	US	1.15	2.18	49.47	0.80
PPI	GER	1.30	2.93	57.45	0.76
CPI	EU	1.12	1.75	48.00	0.72
Retail Sales	GER	1.23	1.68	53.73	0.72
GDP Final	UK	1.00	1.49	41.64	0.68
Nationwide House Prices	UK	1.08	1.79	46.02	0.67
M2	JAP	1.37	2.44	61.42	0.65
Household Consumption	FRA	1.12	2.24	48.12	0.65
Trade Balance	JAP	1.33	2.12	59.29	0.63
PPI	US	0.88	1.41	35.99	0.59
Business Inventories	US	0.82	1.40	33.20	0.55
Chicago Ntl. Activity Index	US	0.80	1.30	32.28	0.54
Tokyo Dept. Store Sales	JAP	1.08	1.43	45.87	0.50
Trade Balance	FRA	0.88	1.34	35.81	0.49
Industrial Production	FRA	0.86	1.38	35.20	0.48
Import Prices	US	0.71	1.30	28.25	0.47
FX Reserves	JAP	0.95	1.49	39.44	0.43

Table 3.5.1.6. Significant Announcement Effects for EUR-JPY Using Spline Model.

ANNOUNCEMENT	COUNTRY	COEFF	ROBUST T	% JUMP	% DAILY
Employment Report	US	3.14	5.84	210.41	5.39
FOMC Fed. Funds	US	4.00	4.65	324.11	5.06
GDP	JAP	3.21	5.04	219.31	2.02
Philadelphia Fed. Index	US	2.35	5.04	133.83	2.00
ECB Interest Rate	EU	1.96	2.98	103.03	1.86
Durable Goods Orders	US	1.99	3.54	105.24	1.62
GDP Preliminary	US	1.90	3.05	98.90	1.54
Industrial Production	UK	1.90	3.44	98.72	1.53
Michigan Sentiment Final	US	1.88	2.52	97.08	1.51
COL Final	GER	2.13	3.50	115.49	1.47
GDP Provisional	UK	1.79	1.66	91.20	1.43
Michigan Sentiment Prelim.	US	1.79	3.21	90.96	1.43
IFO Business Expectations	GER	1.57	2.00	76.00	1.22
Non-Farm Payrolls Final	FRA	1.75	2.29	87.89	1.15
Existing Home Sales	US	1.44	2.15	68.08	1.10
Trade Balance	US	1.40	1.92	66.00	1.07
Current Account	US	1.37	1.84	63.99	1.04
GDP Final	UK	1.21	1.86	54.89	0.91
New Home Sales	US	1.18	1.51	53.06	0.88
Trade Final	EU	1.23	3.23	56.09	0.86
BOJ Monetary Policy	JAP	1.65	2.18	81.31	0.86
Chicago PMI	US	1.13	1.52	50.44	0.84
Factory Inventories/Orders	US	1.12	1.64	49.90	0.83
HCPI	EU	1.16	1.58	52.25	0.81
Consumer Confidence	US	1.03	2.03	45.22	0.76
PPI	US	1.00	1.69	43.49	0.73
Industrial Production	EU	1.06	2.07	46.43	0.73
Labour Costs Prelim.	EU	1.05	1.38	46.36	0.72
Current Account	EU	0.91	1.45	38.99	0.66
Business Inventories	US	0.91	1.60	38.77	0.66
Retail Sales	US	0.89	1.50	37.69	0.64
CPI	EU	0.93	1.53	39.85	0.63
Nationwide House Prices	UK	0.92	1.62	39.58	0.60
Import Prices	US	0.83	1.58	35.05	0.60
PPI	GER	0.94	2.11	40.42	0.57
Chicago Ntl. Activity Index	US	0.78	1.32	32.58	0.56
Tokyo Dept. Store Sales	JAP	1.12	1.55	49.62	0.55
M2	JAP	1.11	2.02	49.12	0.55
Retail Sales	GER	0.90	1.29	38.58	0.55
M4 Provisional	UK	0.75	1.53	30.90	0.53
Household Consumption	FRA	0.86	1.72	36.51	0.52
Trade Balance	JAP	1.05	1.73	46.10	0.52
PSNCR	UK	0.67	1.46	27.46	0.48

Figure 3.5.1.3. Volatility Response Patterns for EUR-JPY.





Japanese GDP is the only Japanese announcement appearing in the top 20, but as the third largest cumulative response it causes vigorous movements in EUR-JPY, the incremental instantaneous volatility reactions measuring 255% and 219% and the cumulative response calculated as 2.21% and 2.02% for FFF and cubic splines, respectively. Of the 20 releases causing the largest cumulative volatility responses, 18 are common to both tables and the FFF specification understates 14 of the 20 compared to the cubic spline specification.

3.6 INFORMATION CONTENT OF NEWS RELEASES

This final section extends the analysis to investigate the extent to which the information surprise of macroeconomic news announcements explains the dynamic behaviour of exchange rate returns in the intervals surrounding the data releases. Since the units of measurement differ across announcements, the approach adopted here follows Andersen, Bollerslev, Diebold and Vega (2003) and Balduzzi et al. (2001) in using standardised news to allow meaningful comparisons across exchange rates and announcement types. Specifically, the standardised news associated with indicator k on day t in interval n is defined as:

$$S_{k,t,n} = \frac{A_{k,t,n} - E_{k,t,n}}{\hat{\sigma}_k}, \tag{3.19}$$

where $A_{k,t,n}$ denotes the announced value of indicator k, $E_{k,t,n}$ represents market expectations of indicator k as measured by the MMS median forecast, and $\hat{\sigma}_k$ is the sample standard deviation of the surprise component, $A_{k,t,n} - E_{k,t,n}$.[42] $\hat{\sigma}_k$ is constant for any indicator k so this standardisation affects neither estimated response coefficients nor the fit of regressions in the analysis which follows, compared to the results based on raw surprises.

[42] The use of standardised news limits our sample to only those indicators that have an MMS expected value. Although there are no survey expectations of interest rate announcements in this sample, these expectations have been inferred from futures prices for the US, Eurozone and UK. Japanese nominal interest rates remained at zero for the duration of the sample, but the Bank of Japan did announce changes to liquidity conditions and adaptive expectations are used for these announcements. The sample therefore includes a total of 122 different macroeconomic indicators separated into 35 for the US, 21 for the Eurozone, 17 for Germany, 18 for France, 18 for the UK and 13 for Japan.

3.6.1 News Impact Effects

To focus on the importance of news at the time of announcements, the following simple regression model is estimated:

$$R_{t,n} = \alpha_k + \beta_k S_{k,t,n} + \in_{t,n}, \tag{3.20}$$

where $R_{t,n}$ denotes the five-minute return for either EUR-USD, EUR-GBP or EUR-JPY from time t,n to $t,n+1$, $S_{k,t,n}$ refers to the standardised news for announcement k (k=1,….,122) at time t,n, and the estimates are based only on those observations ($R_{t,n}$, $S_{k,t,n}$) such that an announcement was made at time t,n. The estimated instantaneous responses, $\hat{\beta}_k$, together with the R^2 of each regression are reported for each indicator in Table 3.6.1.1.

There are a number of striking features that are evident in Table 3.6.1.1. First, confirming the results reported in section 3.5.3 and the findings documented by Andersen, Bollerslev, Diebold and Vega (2003), spot foreign exchange markets are highly responsive to US macroeconomic news surprises immediately following announcements. Coefficients on US macroeconomic variables are often large and highly statistically significant. For example, for a one standard deviation surprise in Consumer Confidence, GDP Advance and Non-Farm Payrolls the Euro depreciates (if positive) or appreciates (if negative) against the Dollar by 0.11%, 0.17%, and 0.11%, respectively. Positive (negative) surprises in the Unemployment Rate result in an appreciation (depreciation) of EUR against USD by 0.16%. These values are entirely consistent with the findings of Andersen, Bollerslev, Diebold and Vega (2003) and represent sizeable moves from statistical and economic perspectives. Second, the signs of the coefficients are entirely consistent with a variety of exchange rate determination models indicating that unexpected strength in the US economy leads to Dollar appreciation relative to the Euro and vice versa. Third, where an indicator displays a significant coefficient, the R^2 reported for regression (3.20) tends to be large, often above 0.2 and reaching 0.6 and 0.7 in some instances. This shows that news surprises on macroeconomic fundamentals explain large proportions of the large jumps in exchange rates in the intervals immediately following their announcement. There is a clear impact effect for many US macroeconomic indicators.

Table 3.6.1.1. News Impact Effects.

ANNOUNCEMENT	EUR-USD		EUR-GBP		EUR-JPY	
	β_k	R^2	β_k	R^2	β_k	R^2
US NEWS						
Business Inventories	-0.0055	0.0119	0.0019	0.0043	-0.0007	0.0003
Capacity Utilisation	-0.0237	0.1302	-0.0115	0.0534	-0.0158	0.0946
Chicago PMI	**-0.0397***	0.1810	-0.0049	0.0161	-0.0266	0.0509
Construction Spending	**-0.0708****	0.3495	**-0.0286****	0.2672	-0.0229	0.0869
Consumer Confidence	**-0.1117****	0.4265	**-0.0557****	0.4124	**-0.0212***	0.1032
Consumer Credit	0.0003	0.0001	0.0009	0.0010	0.0123	0.0843
CPI	-0.0195	0.0804	-0.0070	0.0448	-0.0054	0.0175
Durable Goods Orders	**-0.0814****	0.6291	**-0.0428****	0.5707	-0.0207	0.1468
Existing Home Sales	-0.0083	0.0083	0.0054	0.0099	0.0021	0.0009
Export Price Index	-0.0123	0.0356	-0.0029	0.0049	-0.0025	0.0093
Factory Orders	**-0.0370+**	0.1287	-0.0238	0.2340	**-0.0244+**	0.1614
GDP Advance	**-0.1708***	0.5887	**-0.0841***	0.5893	**-0.0728***	0.5085
GDP Final	0.0026	0.0031	-0.0046	0.1906	-0.0029	0.0069
GDP Preliminary	**-0.0859***	0.7026	**-0.0446***	0.6836	**-0.0452+**	0.6109
Housing Starts	**-0.0263+**	0.0962	-0.0059	0.0180	-0.0054	0.0066
Import Price Index	-0.0097	0.0224	-0.0066	0.0253	-0.0006	0.0005
Industrial Production	-0.0189	0.0828	-0.0128	0.0666	0.0021	0.0017
ISM (Manufacturing)	**-0.0721***	0.2389	**-0.0375***	0.2713	**-0.0384****	0.1701
Leading Indicators	**-0.0330****	0.2112	-0.0129	0.0752	**-0.0360****	0.3024
Michigan Sentiment Final	0.0175	0.0226	-0.0037	0.0039	0.0510	0.0843
Michigan Sentiment Preliminary	0.0149	0.0371	0.0048	0.0059	-0.0028	0.0025
New Home Sales	0.0021	0.0004	0.0046	0.0047	-0.0020	0.0002
Non-Farm Payrolls	**-0.1118+**	0.2181	**-0.0530***	0.1893	**-0.0426***	0.1879
Personal Consumption Expenditure	**-0.0326***	0.1658	-0.0001	0.0000	-0.0200	0.1836
Personal Income	0.0097	0.0148	0.0014	0.0010	-0.0001	0.0000
Philadelphia Fed Index	**-0.0568****	0.2130	**-0.0218****	0.1356	-0.0165	0.0512
PPI	-0.0085	0.0036	0.0119	0.0245	0.0046	0.0051
Productivity Preliminary	-0.0095	0.0416	-0.0001	0.0000	0.0073	0.0169
Productivity Revised	-0.0059	0.0037	0.0162	0.2841	-0.0101	0.0173
Retail Sales	**-0.0867****	0.3828	**-0.0365***	0.2455	**-0.0454****	0.3642
Trade Balance	**-0.0919****	0.4526	**-0.0478****	0.5419	**-0.0355****	0.2247
Treasury Budget	-0.0090	0.0641	0.0004	0.0002	0.0059	0.0347
Unemployment Rate	**0.1576****	0.4332	**0.0667***	0.2997	**0.0560***	0.3239
Initial Claims	**0.0357****	0.1113	**0.0107+**	0.0380	**0.0136***	0.0500
FOMC	-0.0301	0.0635	-0.0009	0.0002	**-0.0202***	0.3256
EU NEWS						
Business Climate Index	0.0114	0.0667	0.0005	0.0002	**-0.0135+**	0.1631
Business Confidence Index	0.0118	0.0761	0.0065	0.0305	0.0017	0.0023
Composite Index	-0.0012	0.0015	-0.0027	0.0078	0.0006	0.0002
Consumer Confidence	0.0050	0.0139	0.0006	0.0003	-0.0081	0.0519
CPI	-0.0127	0.1242	0.0119	0.1165	0.0054	0.0170
Current Account	-0.0105	0.0407	-0.0103	0.0959	**-0.0366****	0.4433
GDP Preliminary	0.0071	0.0696	0.0105	0.1264	0.0011	0.0175
GDP Revised	0.0016	0.0170	-0.0071	0.0863	-0.0003	0.0001
HCIP	0.0039	0.0219	0.0038	0.0219	0.0000	0.0000
Industrial Production	0.0053	0.0278	0.0044	0.0375	0.0113	0.0543
Labour Costs Preliminary	-0.0313	0.4271	-0.0201	0.4194	-0.0154	0.2109
Lab Costs Revised	**0.0209****	0.4571	**-0.0339****	0.6560	**0.0155***	0.2556

Table 3.6.1.1. (Continued)

ANNOUNCEMENT	EUR-USD		EUR-GBP		EUR-JPY	
	β_k	R^2	β_k	R^2	β_k	R^2
EU NEWS (Continued)						
M3	0.0099	0.0512	0.0058	0.0214	0.0153	0.0933
PPI	-0.0039	0.0055	-0.0045	0.0132	0.0119	0.1172
PMI	0.0093	0.0430	0.0013	0.0008	-0.0001	0.0000
Retail Sales	**0.0091***	0.1931	-0.0113	0.1369	0.0019	0.0025
Sentiment Index	0.0193	0.1782	0.0065	0.0267	-0.0009	0.0006
Services Index	-0.0013	0.0015	0.0014	0.0017	-0.0081	0.0407
Trade Balance Preliminary	-0.0055	0.0155	0.0029	0.0063	-0.0074	0.0348
Unemployment	-0.0097	0.0634	-0.0084	0.0727	0.0005	0.0003
ECB	0.0299	0.0847	0.0309	0.1257	0.0291	0.1251
GERMAN NEWS						
Current Account	0.0031	0.0089	0.0003	0.0001	0.0050	0.0296
Employment	-0.0203	0.1993	0.0053	0.0525	**-0.0248***	0.1829
IFO Business Expectations	**0.0441****	0.3014	**0.0205***	0.1842	**0.0272***	0.1549
IFO Current Conditions	-0.0012	0.0002	-0.0015	0.0010	0.0110	0.0256
Import Prices	0.0025	0.0061	0.0086	0.0653	-0.0003	0.0002
Industrial Production	0.0083	0.0347	**-0.0092+**	0.0776	0.0029	0.0105
Manufacturing Orders	0.0126	0.0707	-0.0003	0.0001	0.0099	0.0568
PPI	-0.0014	0.0042	0.0046	0.0104	-0.0031	0.0102
COL Preliminary	0.0008	0.0004	-0.0035	0.0097	-0.0028	0.0041
COL Final	-0.0105	0.0832	-0.0071	0.0369	-0.0096	0.0327
PMI	0.0041	0.0093	0.0137	0.0897	0.0062	0.0256
Retail Sales	0.0152	0.1654	-0.0040	0.0094	0.0178	0.1691
Services Index	**0.0174+**	0.1663	0.0067	0.0364	0.0106	0.0650
Trade Balance	-0.0053	0.0274	-0.0100	0.0856	-0.0038	0.0170
Unemployment	-0.0095	0.0877	-0.0085	0.0424	-0.0182	0.1338
ZEW Expectations	**0.0304***	0.2748	0.0113	0.0788	**0.0299***	0.3655
GDP	-0.0006	0.0005	-0.0034	0.0734	0.0241	0.3901
FRENCH NEWS						
Business Climate	0.0118	0.1178	-0.0065	0.0308	-0.0025	0.0087
CPI Final	0.0053	0.0137	**0.0063***	0.0260	0.0070	0.0370
CPI Preliminary	-0.0055	0.0240	**0.0135+**	0.2845	-0.0077	0.0359
Current Account	-0.0106	0.1001	**0.0103***	0.1807	-0.0117	0.1592
GDP Final	0.0086	0.2072	0.0121	0.2503	-0.0053	0.0169
GDP Preliminary	0.0023	0.0043	**-0.0257+**	0.2989	0.0081	0.2513
Housing Construction	-0.0102	0.0732	-0.0097	0.0872	-0.0032	0.0077
Household Survey	-0.0095	0.0320	-0.0075	0.0516	-0.0050	0.0086
Industrial Production	-0.0037	0.0089	0.0061	0.0339	0.0007	0.0006
Manufacturing	0.0056	0.0201	0.0088	0.0693	0.0082	0.0699
Non-Farm Payrolls Final	-0.0340	0.1556	-0.0191	0.1640	0.0259	0.1119
Non-Farm Payrolls Preliminary	0.0060	0.0107	0.0055	0.0503	-0.0082	0.0607
PPI	0.0054	0.0099	0.0190	0.1129	0.0007	0.0003
PMI	0.0097	0.0524	0.0079	0.0302	**0.0156****	0.1312
Services Index	-0.0045	0.0161	0.0145	0.1279	0.0046	0.0103
Trade Balance	-0.0083	0.0465	0.0006	0.0003	-0.0182	0.1637
Unemployment	0.0051	0.0144	-0.0036	0.0079	-0.0046	0.0182
Job Seekers	-0.0036	0.0068	-0.0062	0.0219	-0.0089	0.0641

Table 3.6.1.1. (Continued)

ANNOUNCEMENT	EUR-USD		EUR-GBP		EUR-JPY	
	β_k	R^2	β_k	R^2	β_k	R^2
UK NEWS						
Average Earnings	-0.0033	0.0076	0.0008	0.0003	0.0081	0.0539
Balance of Trade	-0.0012	0.0012	**-0.0177***	0.2048	0.0084	0.0445
Consumer Credit	0.0078	0.0462	0.0061	0.0313	-0.0011	0.0004
Current Account	**-0.0124***	0.4359	-0.0122	0.1290	-0.0041	0.0337
HCPI	0.0021	0.0064	-0.0052	0.0246	-0.0081	0.0928
GDP Final	-0.0001	0.0000	0.0169	0.2458	**-0.0131****	0.3394
GDP Preliminary	-0.0176	0.2753	**-0.0162***	0.0793	0.0169	0.1728
GDP Provisional	-0.0041	0.0080	-0.0191	0.1634	0.0213	0.2555
Industrial Production	0.0035	0.0051	**-0.0543****	0.2994	0.0033	0.0060
Manufacturing	0.0058	0.0138	**-0.0568****	0.3274	0.0018	0.0018
PPI Input	0.0060	0.0408	-0.0069	0.0090	0.0027	0.0068
PPI Output	0.0027	0.0084	0.0119	0.0263	-0.0020	0.0038
PSNCR	**-0.0112+**	0.1071	0.0033	0.0044	0.0062	0.0451
Retail Sales	0.0108	0.0609	**-0.0801****	0.7237	0.0078	0.0434
RPI	-0.0081	0.0656	**-0.0272****	0.4643	-0.0063	0.0582
RPIX	-0.0069	0.0478	**-0.0192***	0.2325	-0.0042	0.0255
Unemployment	-0.0027	0.0052	0.0131	0.0690	**0.0117+**	0.1119
MPC	0.0001	0.0000	-0.0231	0.0263	0.0019	0.0022
JAPANESE NEWS						
CPI National	0.0032	0.0282	0.0055	0.0307	0.0017	0.0030
CPI Tokyo	0.0036	0.0359	0.0046	0.0212	0.0072	0.0522
Current Account	0.0048	0.0402	-0.0075	0.0682	0.0120	0.1591
GDP	0.0072	0.1546	**-0.0136***	0.6779	-0.0110	0.0513
Housing Starts	0.0061	0.1062	**0.0090***	0.2559	**0.0167+**	0.2838
Industrial Production	0.0003	0.0002	0.0010	0.0010	**0.0107***	0.3259
Job Offers to Seekers Ratio	-0.0051	0.0782	**-0.0144+**	0.1529	**-0.0066+**	0.1149
M2	-0.0015	0.0029	-0.0019	0.0055	-0.0018	0.0041
Tankan Non-Manufacturing	0.0048	0.0234	0.0069	0.0702	0.0085	0.0146
Tankan Manufacturing	-0.0094	0.0885	**-0.0200+**	0.5917	0.0358	0.2626
Tertiary Index	-0.0012	0.0057	-0.0123	0.0666	-0.0041	0.0156
Unemployment	0.0023	0.0161	0.0114	0.0955	0.0060	0.0953
Bank of Japan	0.0006	0.0002	0.0042	0.0166	0.0024	0.0033

Notes: The table reports the impact response coefficient and the R^2 from equation (3.20). **, * and + denote statistical significance at the 1, 5, and 10% levels, respectively, where significance is assessed using t-statistics calculated using heteroscedasticity and autocorrelation consistent standard errors.

Fourth, the lack of statistically significant instantaneous responses to the announcement of non-US macroeconomic news is somewhat surprising.

This lack of important announcements for German news supports the evidence presented by Andersen and Bollerslev (1998a) and Andersen, Bollerslev, Diebold and Vega (2003), but the new evidence reported here suggests that Eurozone, French and Japanese macroeconomic news also do not exert such an influence on exchange rates as compared to US news. There may be several explanations for these findings. Non-US macroeconomic announcements may be forecasted with greater accuracy than US macroeconomic data, meaning that surprises are relatively smaller in magnitude, which may be due to information leakage in the days or weeks leading up to the announcement. The more stringent restrictions surrounding US macroeconomic announcements ensure that this information leakage does not occur in the US. In addition, these restrictions provide a more structured organisation and timetable to US data announcements than non-US releases. More uncertain release times for non-US announcements may result in lower liquidity around announcements and therefore more muted reactions to the news. UK macroeconomic news announcements tend to be structured in a similar fashion to US announcements, which may reinforce the impact effects illustrated in Table 3.6.1.1. UK news surprises show a greater influence than other non-US announcements, and for EUR-GBP in particular, where positive news is associated with Sterling appreciation relative to the Euro.

Finally, in considering the individual announcements, it is reassuring that the macroeconomic indicators reporting a significant news impact effect, or a jump in conditional exchange rate returns, are also the same indicators causing the largest volatility reactions documented in section 3.5.3. The important US news announcements according to Table 3.6.1.1 are Construction Spending, Consumer Confidence, Durable Goods Orders, GDP Advance, GDP Preliminary, ISM Index (Manufacturing), Leading Indicators, Non-Farm Payrolls, Philadelphia Federal Reserve Index, Retail Sales, Trade Balance, Unemployment Rate and Initial Claims. Of the non-US announcements, the few important ones are Labour Costs Revised for the Eurozone, IFO Business Expectations and ZEW Expectations for Germany, and Trade Balance, GDP Preliminary, Industrial Production, Manufacturing Output, Retail Sales, RPI and RPIX for the UK influencing EUR-GBP only. The only surprising omission from these lists is interest rate announcements. Although announcements by the FOMC, ECB, MPC and Bank of Japan cause dramatic instantaneous and persistent increases in Euro volatility, as evidenced in section 3.5.3, the information content of the announcements do not give rise to an incremental movement in conditional exchange rate returns. This suggests that it is the announcement of interest rates (or liquidity provision in the case of the Bank of Japan) that cause jumps in exchange rates, quite apart from the actual information surprise delivered by the announcement.

3.6.2 Dynamic News Effects

To assess the short-run dynamic response of exchange rates to news announcements, exchange rate returns are modelled as a linear function of I lagged values themselves and J lagged values of news on each of K^c fundamentals, where c references the country of origin of the news announcement such that the dynamic effect of news is assessed separately for announcements from different countries:[43]

$$R_{t,n} = \beta_{0^c} + \sum_{i=1}^{I} \beta_{i^c} R_{t,n-i} + \sum_{k^c=1}^{K^c} \sum_{j=0}^{J} \beta_{k^c,j} S_{k^c,t,n-j} + \varepsilon_{c,t,n} \,. \tag{3.21}$$

where TN = 118,656 such that all observations in the sample are used, and I=J=3 was chosen based on the Schwarz and Akaike information criteria.[44] Following Andersen, Bollerslev, Diebold and Vega (2003), the disturbance term in equation (3.21) is allowed to be heteroscedastic, which is important given the strong evidence, including the earlier findings of this chapter, showing that exchange rate volatility occupies a strict intraday pattern. The full model is therefore estimated in two steps. First, equation (3.21) is estimated by ordinary least squares (OLS), so modelling the impact on returns of news on each announcement K^c from country c. Second, the time-varying volatility of the regression residuals, $\varepsilon_{c,t,n}$, is estimated according to

$$\left|\varepsilon_{c,t,n}\right| = \mu_c + \Pi_c \frac{\hat{\sigma}_t^{FI}}{\sqrt{288}} + \sum_{k^c=1}^{K^c} \sum_{j'=0}^{J'} \beta_{k^c,j'} D_{k^c,t,n-j'} + s_{c,t,n} + u_{c,t,n} \,, \tag{3.22}$$

[43] As previously noted, the total number of macroeconomic indicators per country, K^{US}, K^{EU}, K^{GER}, K^{FRA}, K^{UK}, and K^{JAP}, are 35, 21, 17, 18, 18, and 13 respectively.
[44] Allowance for negative J in order to measure any information leakage before the official release time was made but proved unnecessary.

where $|\varepsilon_{c,t,n}|$ is the absolute value of the residual of equation (3.21) and proxies for the volatility during interval n on day t. The fitted values of equation (3.22) are then used to perform a weighted least squares (WLS) estimation of equation (3.21). Volatility is modelled by a combination of three factors: a highly persistent daily volatility factor, $\hat{\sigma}_t^{FI}$; news announcement effects, $D_{k^c,t,n-j'}$; and intraday volatility patterns and calendar effects, $s_{c,t,n}$. More specifically, $\hat{\sigma}_t^{FI}$ measures the volatility for day t, which is estimated by an AR(1)-FIGARCH(1,d,1) model fitted to a longer sample of daily exchange rate returns as explained in section 3.4. News effects on volatility are modelled by pre-estimating a third order polynomial response pattern over the J' interval event horizon and measuring the extent to which a particular announcement dummy loads onto this pattern.[45] Given the importance of US news on volatility identified in sections 3.3.7 and 3.5.3, the average volatility response pattern in equation (3.22) is calibrated from all US news combined. Specifically, the average response pattern across all US news is estimated as $p_{US}(j') = c_0[1-(j'/J')^3] + c_1 j'[1-(j'/J')^2] + c_2 j'^2[1-(j'/J')]$, where the coefficients c_0, c_1, and c_2 are allowed to vary between the FFF and cubic spline intraday volatility patterns and across currencies. In terms of the notation in equation (3.22), the volatility response coefficient is measured as $\beta_{k^c j'} = \gamma_{k^c} p_{US}(j')$ where $p_{US}(j')$ is the volatility response pattern pre-estimated on all US news combined, and γ_{k^c} is the loading coefficient estimated in equation (3.22) that measures the extent to which indicator k from country c loads onto this average volatility response pattern.[46] Finally, $s_{c,t,n}$ represents calendar effects, the explicit treatment of which is described in section 3.5, together with a model for the distinctive twenty-four hour intraday volatility pattern that is ubiquitous in foreign exchange markets. In order to examine whether volatility responses to macroeconomic news announcements are

[45] On comparison with the use of $|S_{k^c}|$ as the news indicator, simple dummy variables provided a superior fit to the data, indicating that, quite apart from the data surprise conveyed by the news announcement, the very event of macroeconomic news announcements cause volatility reactions. In equation (3.22), announcements made within the same five-minute interval are treated as a single news release leaving a total of 31, 18, 15, 16, 12 and 10 announcement dummies for the US, Eurozone, Germany, France, UK and Japan, respectively. A one-hour response is stipulated for each announcement except the US Employment Report and the Federal Reserve FOMC interest rate announcements, which are allowed a two-hour response.

[46] For versions of (3.22) that analyse the impact of non-US news, US announcements are controlled for in the volatility equation by combining all US releases into one dummy variable.

sensitive to the modelling technique used to capture this intraday volatility pattern, FFF and cubic splines are adopted as alternatives.

As a robustness check, equation (3.21) is also estimated using heteroscedasticity and autocorrelation consistent (HAC) standard errors rather than a parametric representation of volatility dynamics. Given that the heteroscedasticity is of known form, as governed by the interaction of intraday and inter-day volatility patterns, which, as explained in section 3.5, are of great economic importance, preference is given to the WLS approach for the efficient estimation of coefficients in equation (3.21). There are no qualitative differences between the coefficients estimated under both the WLS and HAC frameworks, but there are fewer statistically significant coefficients under the WLS paradigm.

Since there are numerous variables in each regression, rather than display the full regression outputs for each estimation, the following empirical results select the most important features of the models. Figures 3.6.2.1 and 3.6.2.2 plot the average intraday actual absolute residual return obtained from the OLS estimation of equation (3.21), along with the fitted values of the volatility equation (3.22), using the FFF and cubic spline intraday specifications respectively.[47] The plots are also separated into winter time and DST to show that the intraday patterns are shifted to the right by one hour during DST to accommodate these timing conventions. The figures show that both specifications generate excellent fits to the average absolute residual return, which demonstrates the success of these models in capturing the volatility dynamics. Similar to the results illustrated in section 3.5, the cubic spline model tends to offer a more accurate fit to the intraday volatility pattern in relation to the volatility peaks. Table 3.6.2.1 reports the instantaneous response of exchange rate returns to news announcements, $\hat{\beta}_{k^c,0}$, when estimated by WLS and using the entire sample of data. In order to conserve space, the table includes only those announcements generating a statistically significant response at the 5% level for at least one of the three currency pairs. The table confirms the strong influence of news on US macroeconomic fundamentals on exchange rate returns in the five-minute interval immediately following the announcements.

[47] These plots use the residuals from the specification of equation (3.21) that includes only US macroeconomic announcements for illustrative purposes. The plots based on the residuals of other specifications of equation (3.21), reveal an equally impressive fit to the data and are available on request.

Figure 3.6.2.1. Actual and Fitted Intraday Absolute Residuals for FFF Model.

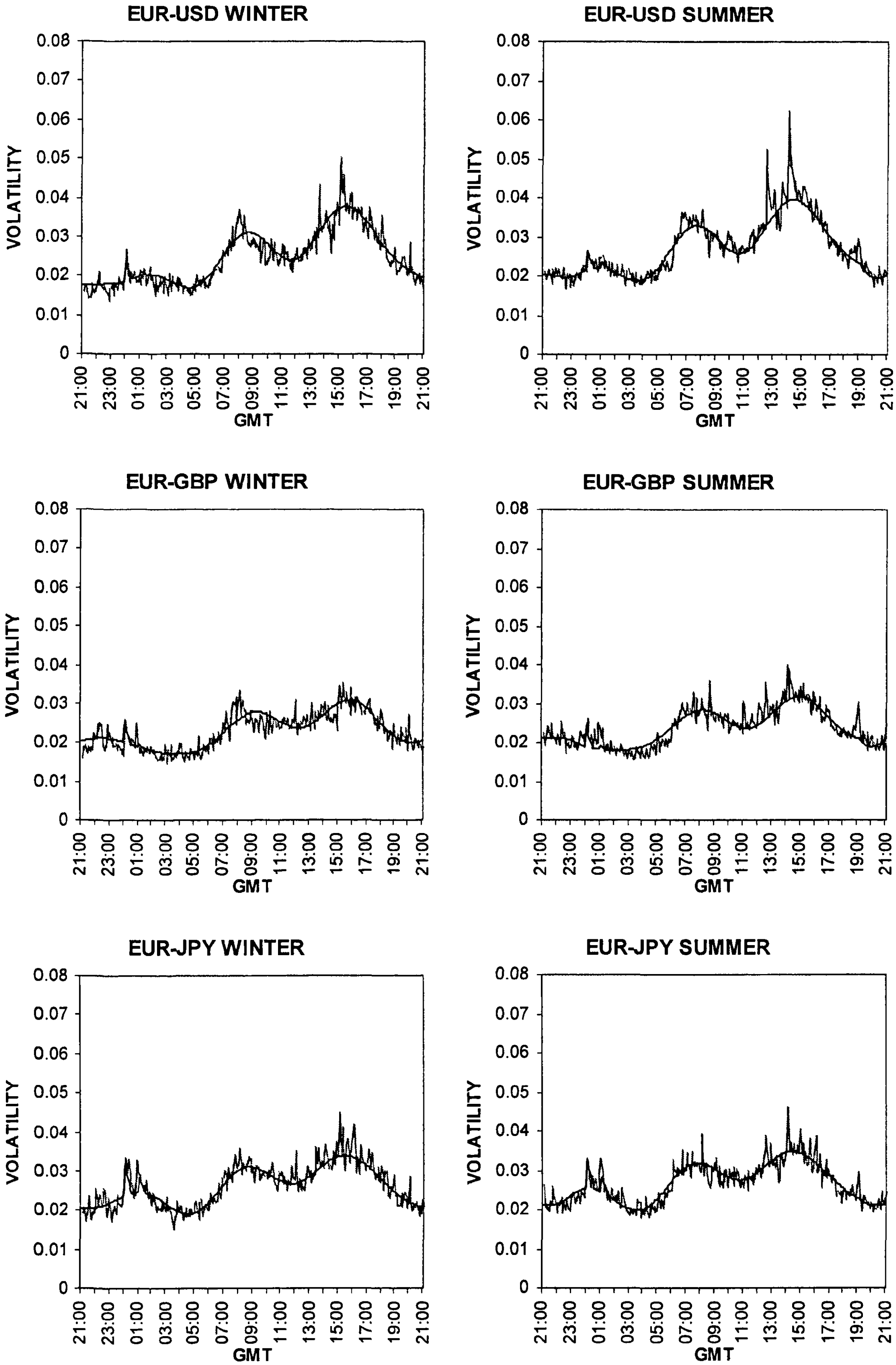


Figure 3.6.2.2. Actual and Fitted Intraday Absolute Residuals for Cubic Spline Model.

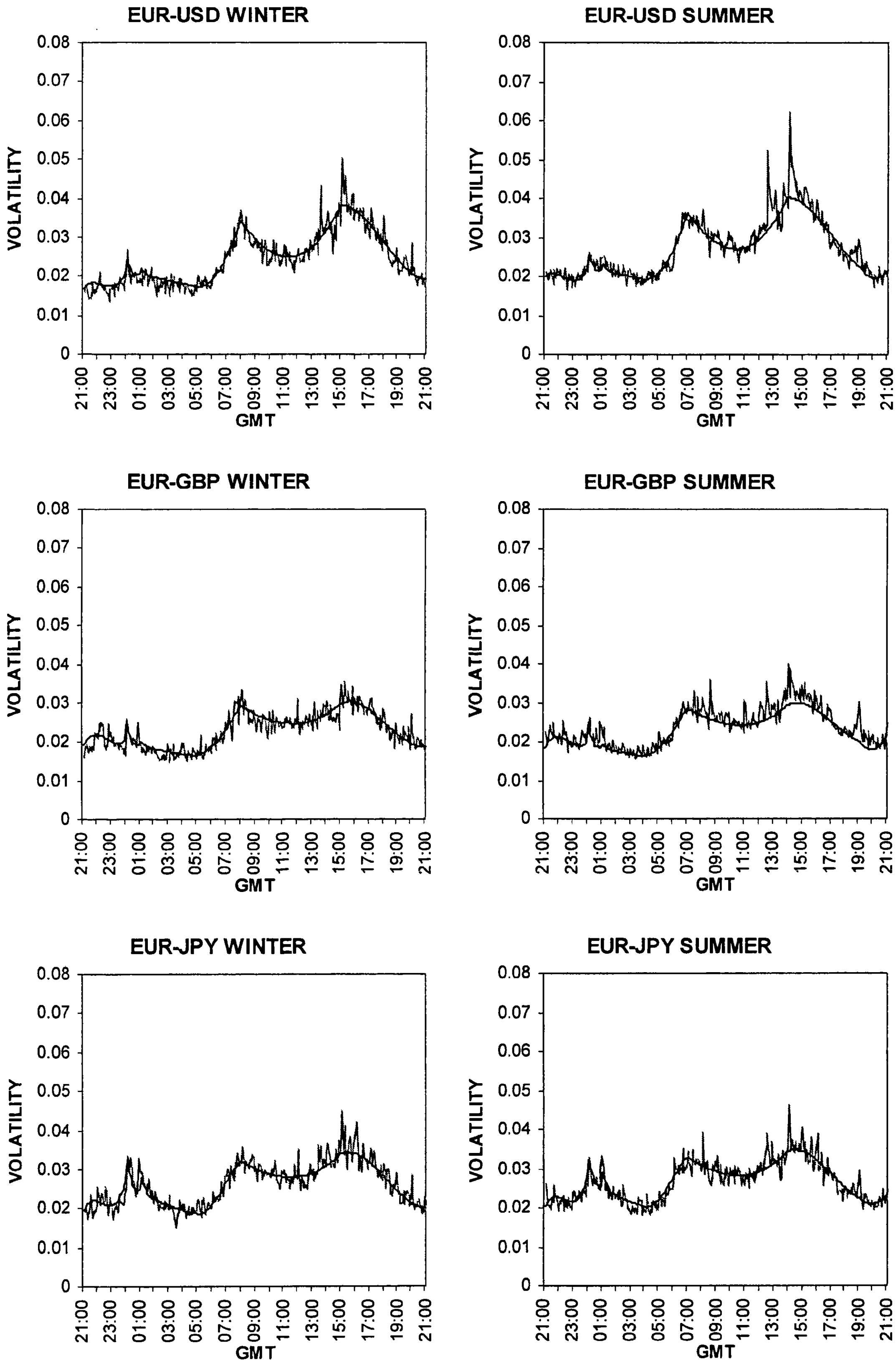


Table 3.6.2.1. Instantaneous Mean Response under WLS Estimation.

ANNOUNCEMENT	EUR-USD		EUR-GBP		EUR-JPY	
	FFF	SPLINE	FFF	SPLINE	FFF	SPLINE
US News						
Capacity Utilisation	-0.0216	-0.0217	-0.0086	-0.0090	**-0.0300***	**-0.0300***
Chicago PMI	**-0.0533****	**-0.0532****	-0.0089	-0.0089	-0.0209	-0.0211
Construction Spending	**-0.0622***	**-0.0618***	-0.0266	**-0.0322+**	0.0118	0.0114
Consumer Confidence	**-0.1285****	**-0.1281****	**-0.0659****	**-0.0672****	-0.0260	-0.0262
Durable Goods Orders	**-0.0886****	**-0.0885****	**-0.0464****	**-0.0465****	-0.0213	-0.0208
GDP Advance	**-0.1634****	**-0.1630****	**-0.0829****	**-0.0825****	**-0.0749****	**-0.0750****
Leading Indicators	**-0.0319***	**-0.0319***	-0.0123	-0.0123	**-0.0355****	**-0.0358****
Michigan Sentiment (Final)	0.0010	0.0006	-0.0064	-0.0053	**0.0472***	**0.0486***
Non-Farm Payrolls	**-0.1045****	**-0.1044****	**-0.0506****	**-0.0508****	-0.0293	-0.0292
Personal Consumption Expenditure	**-0.0345****	**-0.0345****	-0.0060	-0.0060	**-0.0245****	**-0.0252****
Philadelphia Fed Index	**-0.0593***	**-0.0593***	**-0.0239+**	-0.0238	-0.0155	-0.0155
Retail Sales	**-0.0856****	**-0.0863****	**-0.0392****	**-0.0380***	**-0.0508****	**-0.0515****
Trade Balance	**-0.0791****	**-0.0786****	**-0.0361****	**-0.0352****	**-0.0308+**	**-0.0310+**
Unemployment Rate	**0.1167****	**0.1166****	**0.0455****	**0.0440***	**0.0447***	**0.0448***
Initial Claims	**0.0364****	**0.0361****	**0.0114***	**0.0120***	**0.0125***	**0.0124***
Eurozone News						
Current Account	-0.0076	-0.0056	-0.0062	-0.0053	**-0.0339****	**-0.0341****
Labour Costs (Preliminary)	**-0.0355***	**-0.0355***	-0.0214	-0.0212	-0.0066	-0.0074
Labour Costs (Revised)	**0.0216+**	**0.0215+**	-0.0262	-0.0262	**0.0188***	**0.0190***
German News						
Employment	**-0.0211+**	**-0.0213+**	-0.0013	-0.0010	**-0.0265****	**-0.0266****
IFO Business Expectations	**0.0496***	**0.0499***	**0.0214+**	0.0215	**0.0325***	**0.0326***
Retail Sales	**0.0228***	**0.0229***	0.0017	0.0013	**0.0195+**	**0.0198+**
Services Index	**0.0184***	**0.0182***	0.0122	0.0122	0.0123	0.0122
ZEW Expectations	**0.0305****	**0.0302****	0.0148	0.0150	**0.0273****	**0.0274****
French News						
CPI (Preliminary)	-0.0004	-0.0008	**0.0210****	**0.0203****	-0.0054	-0.0056
Manufacturing	**0.0247+**	**0.0271***	0.0088	0.0110	**0.0293+**	**0.0302+**
PPI	0.0060	0.0035	**0.0228***	**0.0213***	-0.0059	-0.0060
Services Index	-0.0039	-0.0042	**0.0211***	**0.0211***	0.0056	0.0057
Trade Balance	-0.0152	**-0.0171+**	-0.0011	-0.0012	**-0.0344****	**-0.0363****
UK News						
Balance of Trade	-0.0046	-0.0046	**-0.0215***	**-0.0216***	0.0082	0.0079
Retail Sales	0.0115	0.0119	**-0.0784****	**-0.0785****	0.0076	0.0079
RPI	-0.0195	-0.0237	**-0.0537****	**-0.0555****	-0.0133	-0.0148
Japanese News						
Housing Starts	0.0042	0.0040	**0.0095***	**0.0093+**	0.0122	0.0123
Industrial Production	-0.0040	-0.0035	-0.0024	-0.0022	**0.0109****	**0.0118****
Tankan (Non Manufacturing)	0.0002	0.0019	-0.0005	**-0.0054****	-0.0060	-0.0067
Tankan (Manufacturing)	-0.0012	-0.0026	**-0.0123****	**-0.0098****	0.0255	0.0258

Notes: The table reports the instantaneous response to news announcements in the WLS estimation of equation (3.21) for the conditional exchange rate return. Only those announcements producing at least one significant coefficient at the 5% level across exchange rates and volatility models are included. **, * and + denote statistical significance at the 1, 5, and 10% levels respectively.

Under the dynamic framework and robust procedures of equations (3.21) and (3.22), the same US indicators as identified in Table 3.6.1.1 produce highly significant coefficient estimates, and for EUR-USD in particular. Therefore, accounting for the volatility dynamics does not diminish the dramatic effect of US news in causing instantaneous jumps in exchange rate returns. Moreover, the differences between the WLS estimates formulated from FFF and cubic spline intraday volatility models are negligible. Immediate responses to US news are much larger for EUR-USD than EUR-GBP or EUR-JPY and it is interesting that data revealing a strengthening US economy generate a depreciation of the Euro against all three currencies. The indicators offering the largest instantaneous return responses are Consumer Confidence, Durable Goods Orders, GDP Advance, Non-Farm Payrolls, Retail Sales, Trade Balance and the Unemployment Rate with coefficient values in accordance with those presented by Andersen, Bollerslev, Diebold and Vega (2003).

In the remainder of Table 3.6.2.1, there are only very few non-US macroeconomic indicators causing instantaneous jumps in the conditional exchange rate mean, which supports the findings of Table 3.6.1.1. News relating to the Eurozone as a whole has barely any effect, whilst stronger than expected German expectations and Retail Sales lead to Euro appreciation. The announcement of inflation in France results in a slight strengthening of the EUR against GBP, but these are very small reactions compared to the influence of US news. As expected given the results of Table 3.6.1.1, the performance of the UK economy also causes movement in the EUR-GBP rate with GBP appreciating strongly against EUR in the intervals directly following larger than expected Retail Sales and RPI figures. Finally, although some coefficients are statistically significant for Japanese news, the coefficient estimates are very small in comparison to the news effects emanating from other countries.

The associated volatility responses derived from equation (3.22) are displayed in Tables 3.6.2.2 and 3.6.2.3, which report the instantaneous reaction of volatility to news announcements, $\beta_{k^c,0}$, and the cumulative volatility reaction, $\sum_{j'=0}^{J'} \beta_{k^c,j'}$, over the response horizon for the FFF and cubic spline specifications of the intraday volatility pattern respectively.

Table 3.6.2.2. Instantaneous and Cumulative Volatility Responses from FFF Model.

ANNOUNCEMENT	EUR-USD		EUR-GBP		EUR-JPY	
	INST	CUM	INST	CUM	INST	CUM
US News						
Chicago PMI	**0.0357****	0.1273	**0.0067***	0.0354	**0.0126****	0.0513
Consumer Confidence	**0.0430****	0.1532	**0.0155****	0.0816	**0.0186****	0.0758
Durable Goods Orders	**0.0146****	0.0521	**0.0070***	0.0367	**0.0082+**	0.0333
Existing Homes Sales	**0.0123****	0.0439	-0.0027	-0.0141	-0.0013	-0.0055
Factory Orders	**0.0194****	0.0693	**0.0054+**	0.0286	**0.0070+**	0.0286
GDP Advance	**0.0445****	0.1587	0.0056	0.0296	0.0027	0.0112
GDP Preliminary	**0.0229****	0.0815	0.0062	0.0327	0.0009	0.0038
Industrial Production	**0.0139****	0.0496	**0.0093****	0.0489	-0.0025	-0.0100
ISM Manufacturing	**0.0499****	0.1780	**0.0229****	0.1211	**0.0470****	0.1915
Michigan Sentiment (Final)	**0.0104***	0.0370	**0.0134****	0.0705	**0.0310****	0.1261
Michigan Sentiment (Prelim)	**0.0275****	0.0979	**0.0159****	0.0838	**0.0172****	0.0699
New Homes Sales	**0.0232****	0.0828	0.0028	0.0145	**0.0191****	0.0779
Philadelphia Fed Index	**0.0440****	0.1570	**0.0109****	0.0575	**0.0244****	0.0995
PPI	**0.0132****	0.0470	0.0004	0.0023	0.0029	0.0117
Retail Sales	**0.0392****	0.1398	**0.0119****	0.0628	0.0054	0.0219
Trade Balance	**0.0342****	0.1219	**0.0056+**	0.0294	**0.0153****	0.0625
Employment Report	**0.0736****	0.4859	**0.0279****	0.2803	**0.0349****	0.2659
Initial Claims	**0.0128****	0.0456	**0.0033+**	0.0175	**0.0056***	0.0230
Federal Reserve FOMC	**0.0772****	0.5093	**0.0309****	0.3104	**0.0284****	0.2161
Eurozone News						
ECB	**0.0422****	0.1506	**0.0217****	0.1147	**0.0263****	0.1071
German News						
IFO Business Expectations	**0.0230****	0.0819	**0.0058+**	0.0307	**0.0096***	0.0392
PPI	-0.0047	-0.0166	**0.0073***	0.0386	0.0009	0.0037
Cost Of Living (Final)	-0.0030	-0.0109	0.0050	0.0262	**0.0150****	0.0611
French News						
Non-Farm Payrolls (Final)	**0.0161***	0.0575	0.0027	0.0142	0.0171	0.0697
UK News						
Industrial Production	**0.0085+**	0.0304	**0.0143****	0.0757	0.0027	0.0111
Retail Sales	0.0033	0.0118	**0.0100****	0.0526	-0.0012	-0.0047
MPC	0.0070	0.0249	**0.0296****	0.1564	**0.0088***	0.0360
Japanese News						
GDP	-0.0060	-0.0214	-0.0082	-0.0433	**0.0215****	0.0864
Industrial Production	**0.0080+**	0.0284	**0.0107****	0.0566	-0.0069	-0.0280
Tankan	-0.0122	-0.0434	-0.0179	-0.0946	**0.0207***	0.0843
Bank Of Japan	0.0042	0.0150	**0.0135****	0.0711	**0.0113****	0.0460

Notes: The table reports the instantaneous ($\beta_{k^c,0} = \gamma_{k^c} p_{US}(0)$) and cumulative responses ($\sum_{j'=0}^{J'} \beta_{k^c,j'}$) to news announcement dummies in equation (3.22), using the FFF specification for the intraday volatility pattern. Only those announcements producing at least one significant loading coefficient (γ_{k^c}) at the 5% level across exchange rates are included. **, * and + denote statistical significance of the loading coefficient at the 1, 5, and 10% levels respectively.

Table 3.6.2.3. Instantaneous and Cumulative Volatility Responses from Spline Model.

ANNOUNCEMENT	EUR-USD		EUR-GBP		EUR-JPY	
	INST	CUM	INST	CUM	INST	CUM
US News						
Chicago PMI	**0.0343****	0.1279	**0.0065***	0.0366	**0.0111***	0.0486
Consumer Confidence	**0.0416****	0.1554	**0.0152****	0.0862	**0.0184****	0.0804
Durable Goods Orders	**0.0166****	0.0620	**0.0078****	0.0444	**0.0096***	0.0420
Existing Homes Sales	**0.0118***	0.0442	-0.0023	-0.0131	-0.0009	-0.0039
Factory Orders	**0.0181****	0.0675	**0.0055+**	0.0310	0.0062	0.0269
GDP Advance	**0.0453****	0.1692	0.0060	0.0342	0.0035	0.0152
GDP Preliminary	**0.0238****	0.0888	0.0067	0.0380	0.0020	0.0086
Industrial Production	**0.0149****	0.0557	**0.0106****	0.0599	-0.0010	-0.0045
ISM Manufacturing	**0.0488****	0.1821	**0.0226****	0.1278	**0.0456****	0.1987
Michigan Sentiment (Final)	**0.0098***	0.0365	**0.0128****	0.0725	**0.0300****	0.1307
Michigan Sentiment (Prelim)	**0.0261****	0.0973	**0.0155****	0.0880	**0.0171****	0.0743
New Homes Sales	**0.0217****	0.0811	0.0029	0.0163	**0.0179****	0.0779
Philadelphia Fed Index	**0.0429****	0.1600	**0.0096****	0.0545	**0.0234****	0.1018
PPI	**0.0139****	0.0519	0.0007	0.0039	0.0038	0.0164
Retail Sales	**0.0394****	0.1471	**0.0123****	0.0696	0.0062	0.0272
Trade Balance	**0.0350****	0.1308	**0.0059+**	0.0334	**0.0157****	0.0684
Employment Report	**0.0739****	0.5127	**0.0280****	0.3026	**0.0353****	0.2893
Initial Claims	**0.0141****	0.0525	**0.0038***	0.0217	**0.0065****	0.0282
Federal Reserve FOMC	**0.0765****	0.5308	**0.0305****	0.3304	**0.0285****	0.2336
Eurozone News						
ECB	**0.0421****	0.1570	**0.0207****	0.1174	**0.0259****	0.1128
German News						
IFO Business Expectations	**0.0251****	0.0936	**0.0072***	0.0407	**0.0109***	0.0473
PPI	-0.0050	-0.0185	**0.0066***	0.0376	-0.0003	-0.0012
Cost Of Living (Final)	-0.0031	-0.0117	0.0042	0.0238	**0.0136****	0.0592
French News						
Non-Farm Payrolls (Final)	0.0124	0.0464	0.0007	0.0042	**0.0149***	0.0647
UK News						
Industrial Production	**0.0109***	0.0408	**0.0149****	0.0844	0.0045	0.0198
Retail Sales	0.0057	0.0215	**0.0109****	0.0619	0.0009	0.0038
MPC	0.0059	0.0220	**0.0272****	0.1543	**0.0083***	0.0362
Japanese News						
GDP	-0.0065	-0.0244	-0.0075	-0.0424	**0.0199***	0.0869
Industrial Production	0.0074	0.0278	**0.0103****	0.0585	-0.0078	-0.0341
Tankan	-0.0128	-0.0478	-0.0176	-0.0995	**0.0172***	0.0749
Bank Of Japan	0.0039	0.0147	**0.0134****	0.0760	**0.0114****	0.0495

Notes: The table reports the instantaneous ($\beta_{k^c,0} = \gamma_{k^c} p_{US}(0)$) and cumulative responses ($\sum_{j'=0}^{J'} \beta_{k^c,j'}$) to news announcement dummies in equation (3.22), using the cubic spline specification for the intraday volatility pattern. Only those announcements producing at least one significant loading coefficient (γ_{k^c}) at the 5% level across exchange rates are included. **, * and + denote statistical significance of the loading coefficient at the 1, 5, and 10% levels respectively.

Volatility responses are included for only those announcements producing a significant loading coefficient in the estimation of equation (3.22).

In support of the previous findings of this chapter, the instantaneous volatility response measures show that US news announcements cause dramatic surges in volatility, and the cumulative volatility response measures show that this initial rise in volatility often persists for a number of five-minute intervals after the announcement. There is clear consistency between Table 3.6.2.1 for the conditional mean and Tables 3.6.2.2 and 3.6.2.3 for volatility in that the US announcements causing the greatest reaction in the conditional mean also cause large volatility responses. Consistent with the evidence presented in section 3.5.3, these same announcements caused the largest volatility responses under a slightly different econometric framework. It is important, however, that there are a number of announcements causing volatile exchange rate reactions, such as Existing and New Home Sales, Factory Orders, Industrial Production, the ISM (Manufacturing) Index, the Michigan Sentiment Index and PPI, but which do not give rise to systematic movements in returns that are related to the information released. This is more heavily emphasised by the consideration of the Federal Reserve's FOMC announcements of interest rate changes, which produces the largest instantaneous and cumulative volatility responses and some of the largest five-minute absolute returns in the entire sample, and yet these returns are not significantly correlated with the standardised measure of interest rate news.

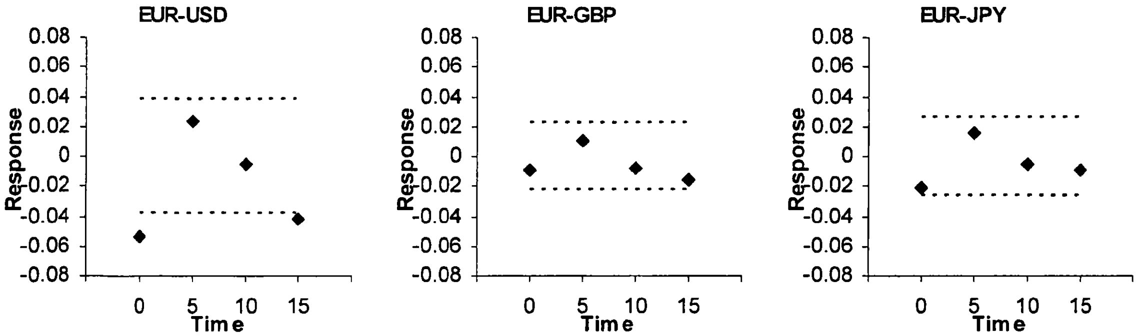
In confirmation of the findings presented in section 3.5.3, there are very few non-US announcements causing surges in Euro volatility. Interest rate decisions by the ECB are the only Eurozone indicator causing sufficiently violent exchange rate reactions to warrant inclusion in Tables 3.6.2.2 and 3.6.2.3 and these reactions occur across all three exchange rate pairs. IFO Business Expectations for Germany are important, whilst UK news, including Industrial Production, Retail Sales and MPC interest rate decisions all provide significant volatility reactions in EUR-GBP, while GDP, Industrial Production, the Tankan Index and Bank of Japan liquidity announcements cause volatile reactions in EUR-JPY. These findings are all supported in both Tables 3.6.2.2 and 3.6.2.3, which show that the measurement of volatility responses is not sensitive to the choice of intraday modelling technique. However, cumulative volatility responses tend to be larger for the cubic spline specification than the FFF model, supporting the evidence of section 3.5.6.

In order to investigate the dynamic impact of macroeconomic news announcements on conditional mean exchange rate returns, Figures 3.6.2.3 to 3.6.2.8 plot the estimated WLS coefficients, $\hat{\beta}_{k^c,j}$, for j=0, 1, 2, 3, for selected announcements, along with two standard error bands above and below the null hypothesis of a zero response to news. Figures 3.6.2.3 to 3.6.2.8 show the dynamic response coefficients for certain US, Eurozone, German, French, UK and Japanese news events respectively. Figure 3.6.2.3 illustrates the very large instantaneous returns reactions to some US announcements. Another striking feature visible from the plots is the rapidity of the adjustment in the conditional mean. Response coefficients at five, ten and fifteen minutes following the announcement are very rarely large or statistically significant, suggesting that the majority of the reaction occurs in the five-minute interval containing the announcement. This very quick conditional mean jump contrasts with the volatility responses, which tend to linger for up to an hour, and sometimes two hours, after the announcement. For many of the announcements included in Figure 3.6.2.3 the second response coefficient has the same sign as the first coefficient, but it is much smaller in magnitude and is very rarely statistically significant, showing that the price reaction five minutes after the announcement is in the same direction as the instantaneous response. The price adjustment process is therefore very fast with the information seemingly interpreted consistently in the following immediate intervals. The announcements exerting greatest influence on Euro exchange rate returns, and EUR-USD returns in particular are Consumer Confidence, Durable Goods Orders, GDP Advance, Non-Farm Payrolls, Retail Sales, Trade Balance and the Unemployment rate, entirely consistent with existing evidence.

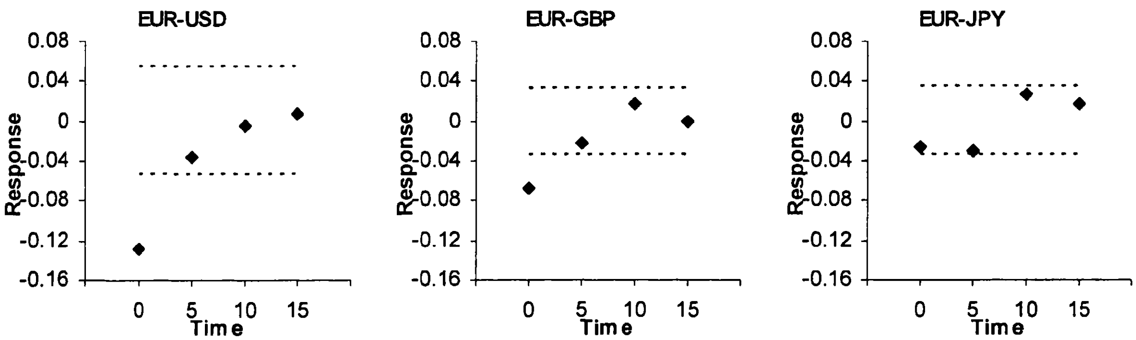
Although instantaneous coefficients are much smaller in Figures 3.6.2.4 to 3.6.2.8, and there are fewer statistically significant coefficients, the dynamic response patterns are very similar for non-US news announcements. Announcements of particular importance to the value of the Euro are Eurozone GDP Preliminary (although the reaction occurs five minutes after the announcement rather than instantaneously), German IFO and ZEW Expectations and UK Retail Sales and RPI.

Figure 3.6.2.3. Dynamic Mean Response to US News.

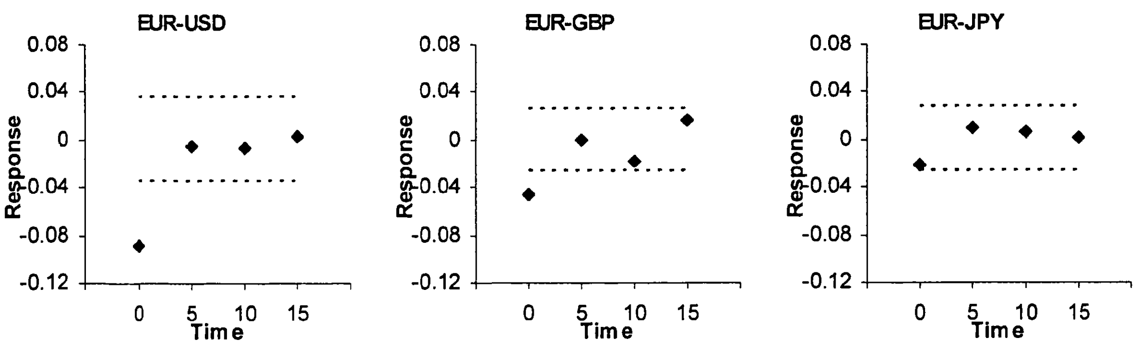
Chicago PMI



Consumer Confidence



Durable Goods Orders



GDP Advance

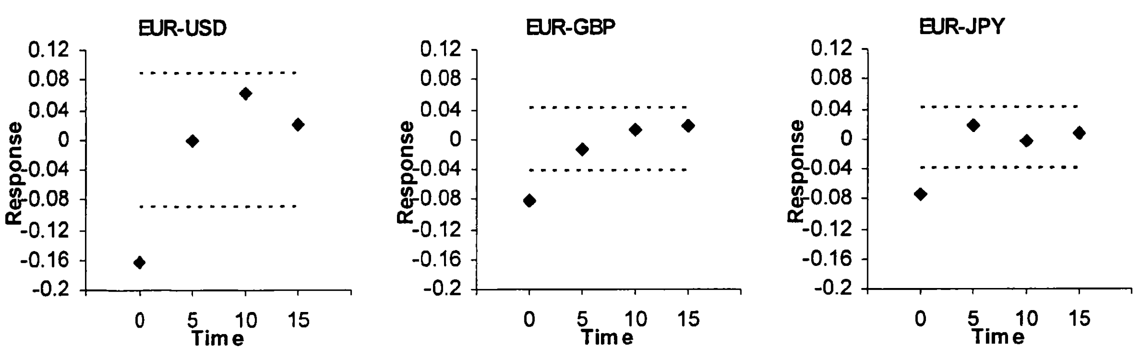
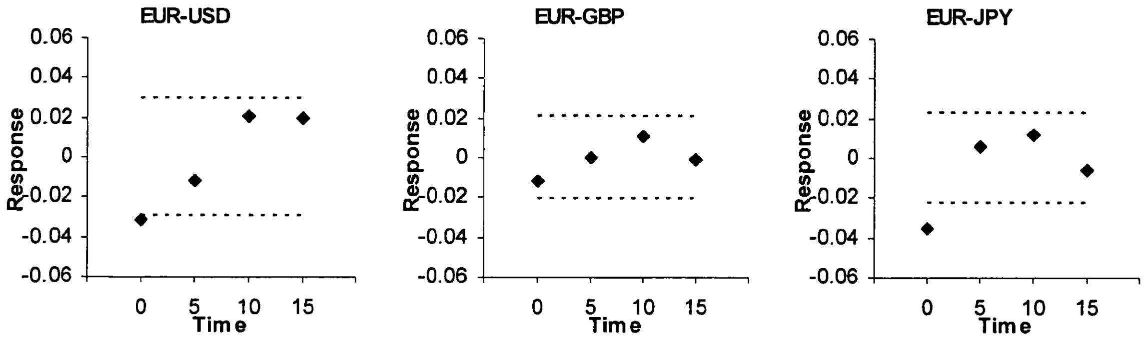
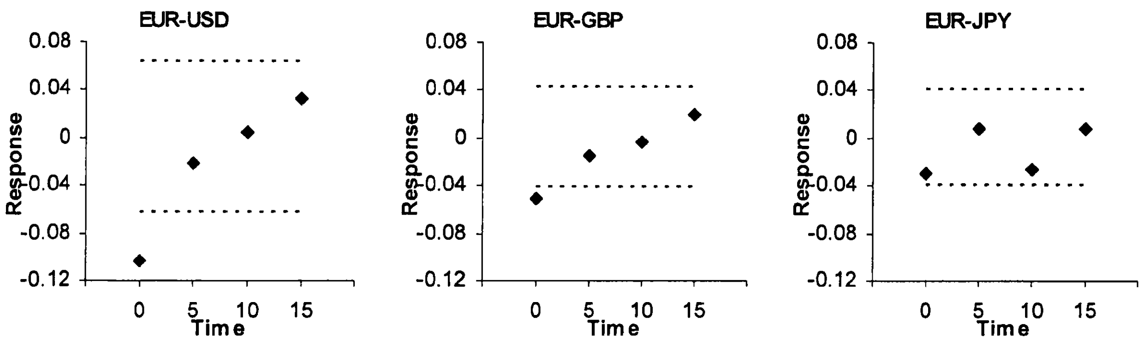


Figure 3.6.2.3. (Continued)

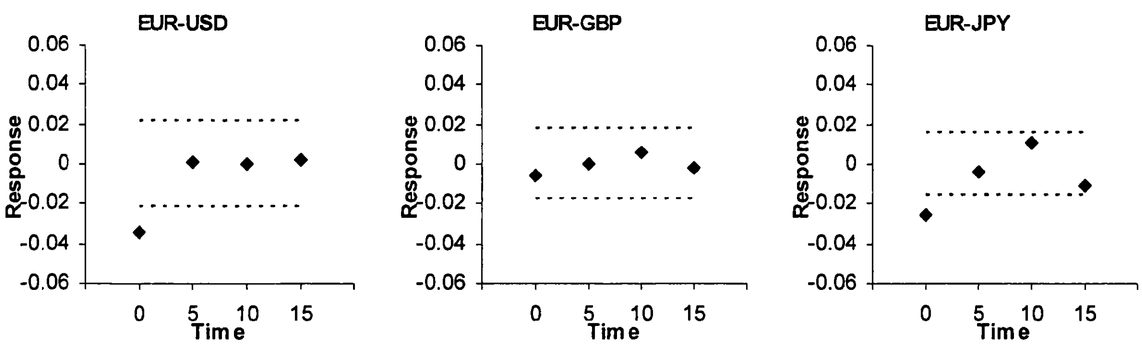
Leading Indicators



Non-Farm Payrolls



Personal Consumption Expenditure



Philadelphia Federal Reserve Index

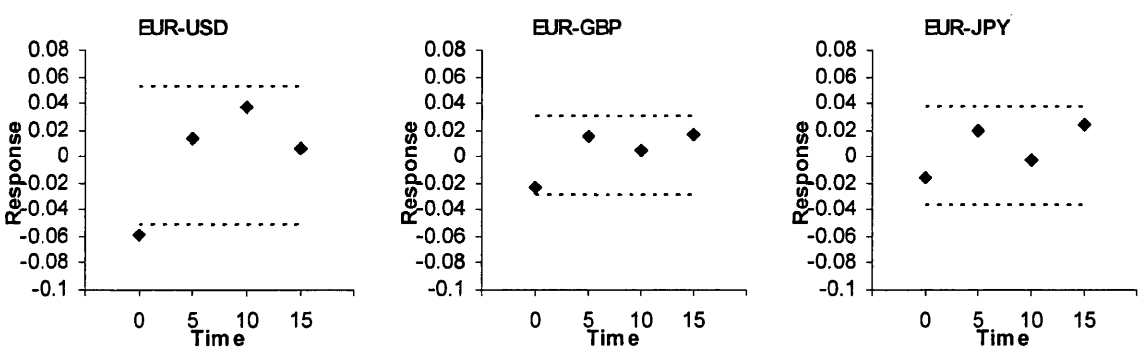
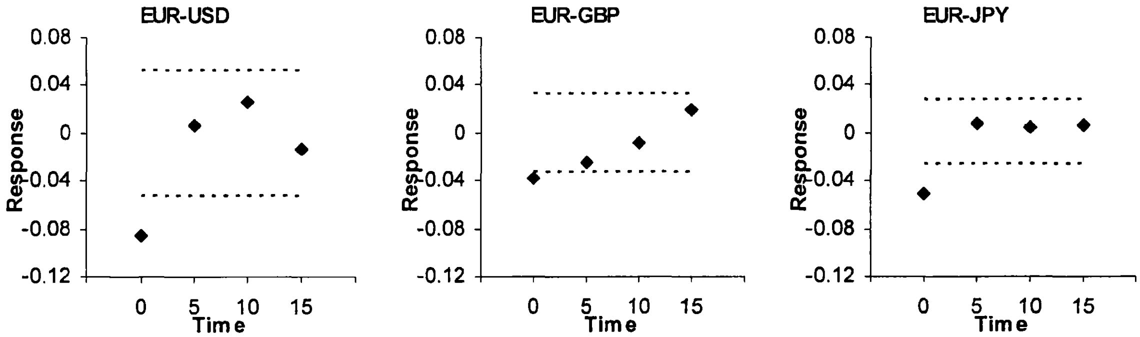
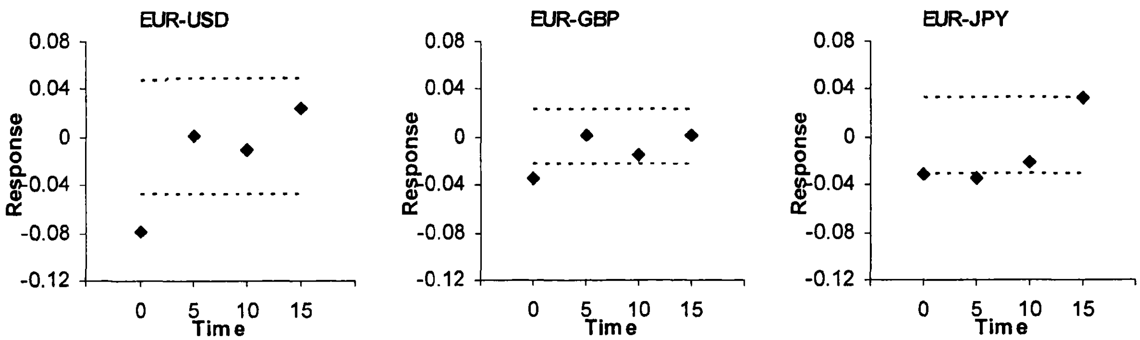


Figure 3.6.2.3. (Continued)

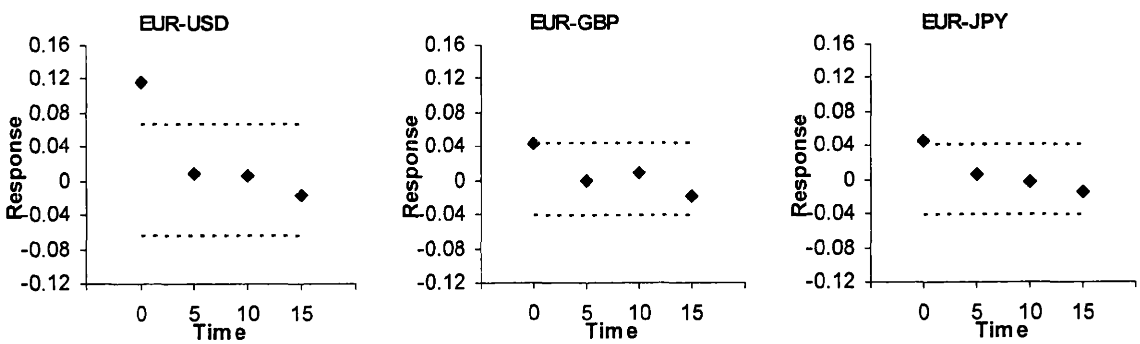
Retail Sales



Trade Balance



Unemployment Rate



Initial Claims

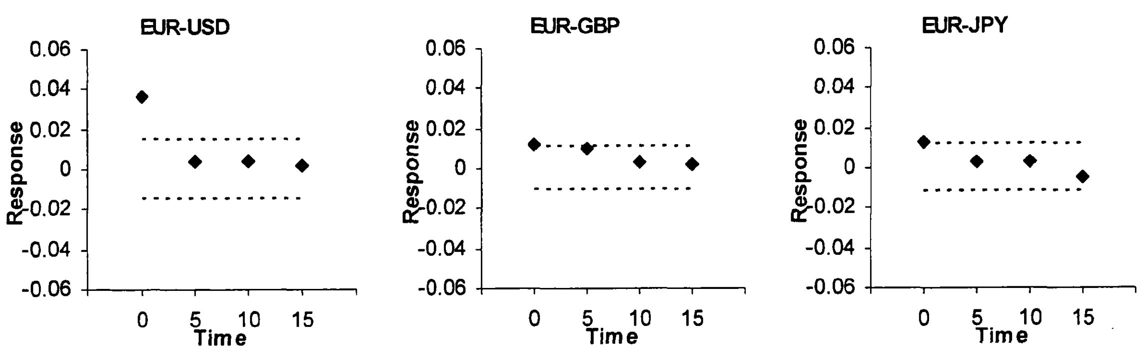
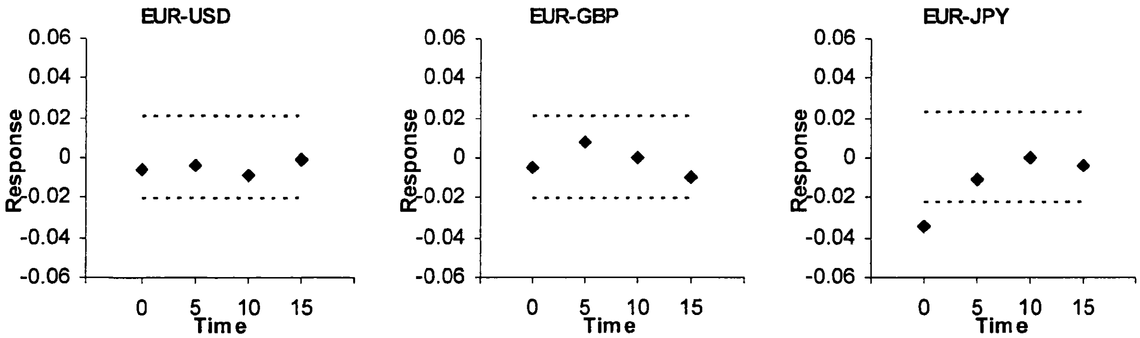
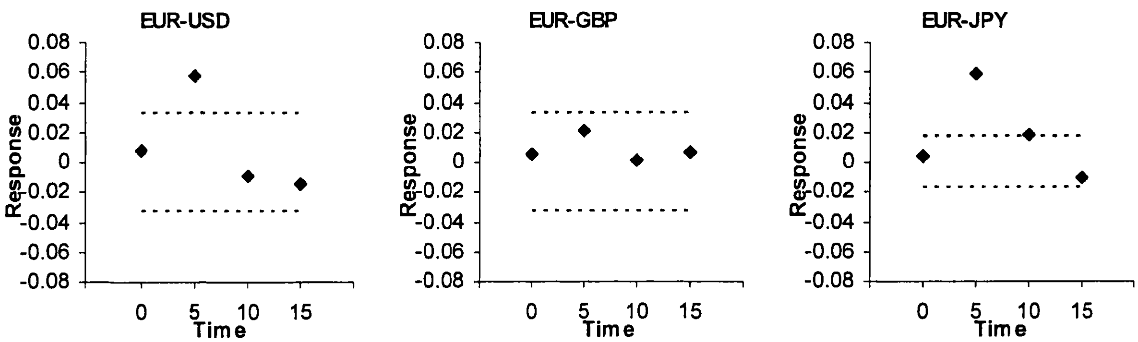


Figure 3.6.2.4. Dynamic Mean Response to Eurozone News.

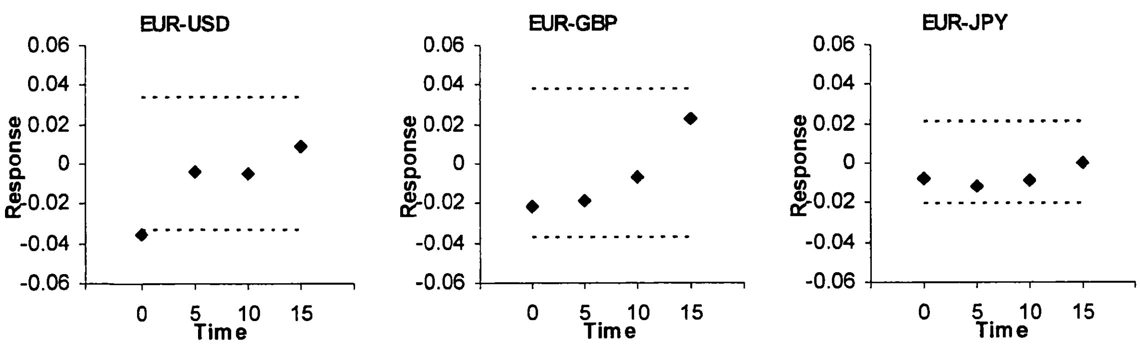
Current Account



GDP Preliminary



Labour Costs Preliminary



Labour Costs Revised

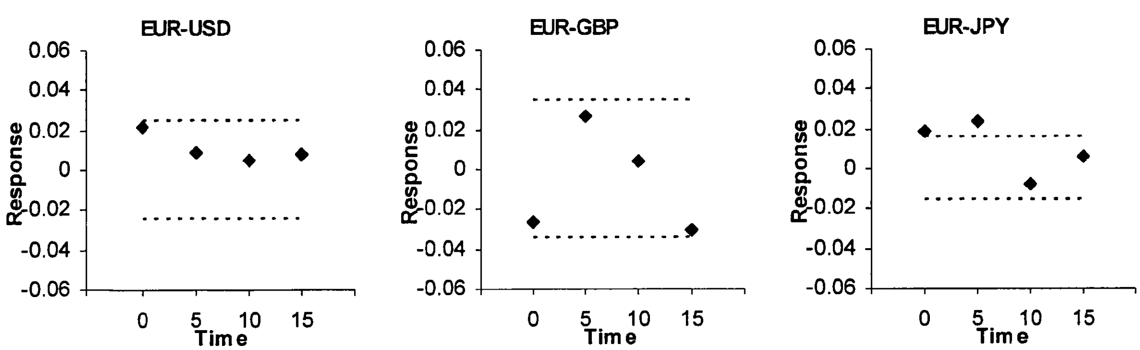
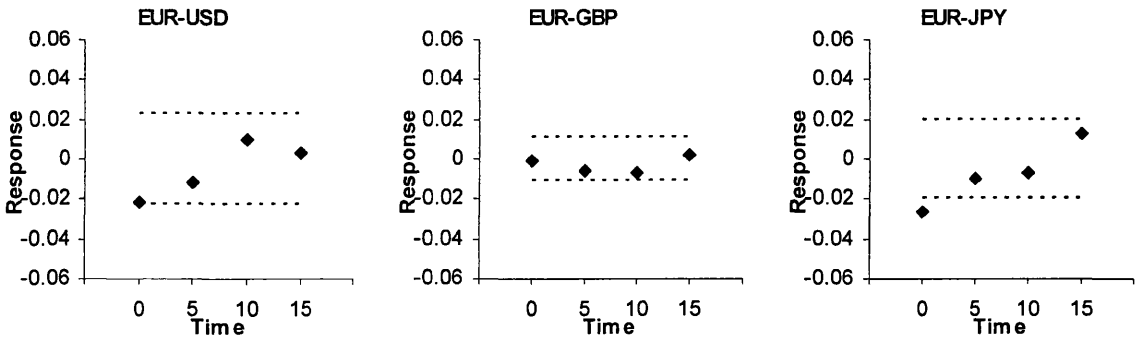
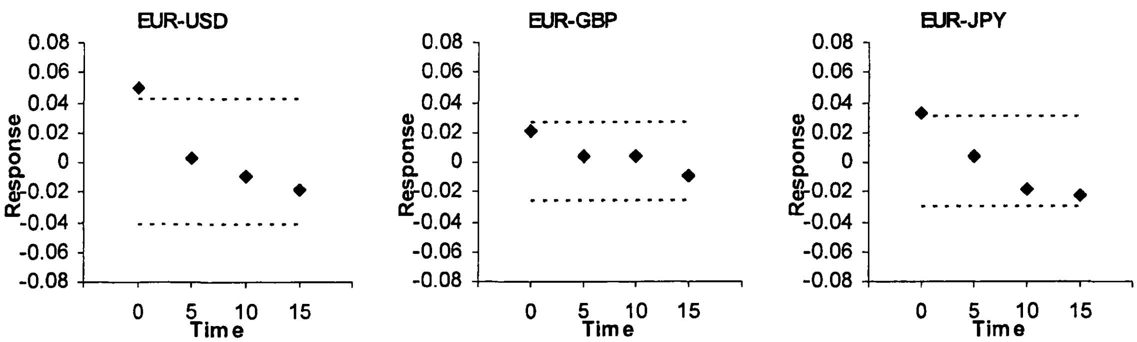


Figure 3.6.2.5. Dynamic Mean Response to German News.

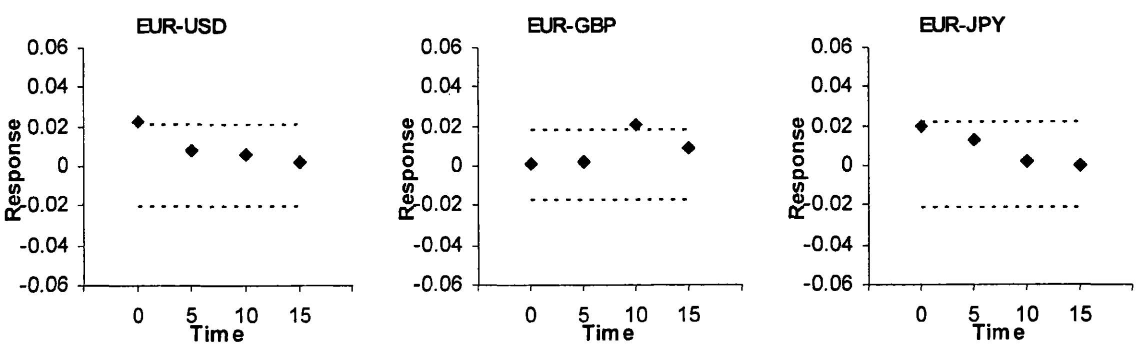
Employment



IFO Business Expectations



Retail Sales



ZEW Expectations

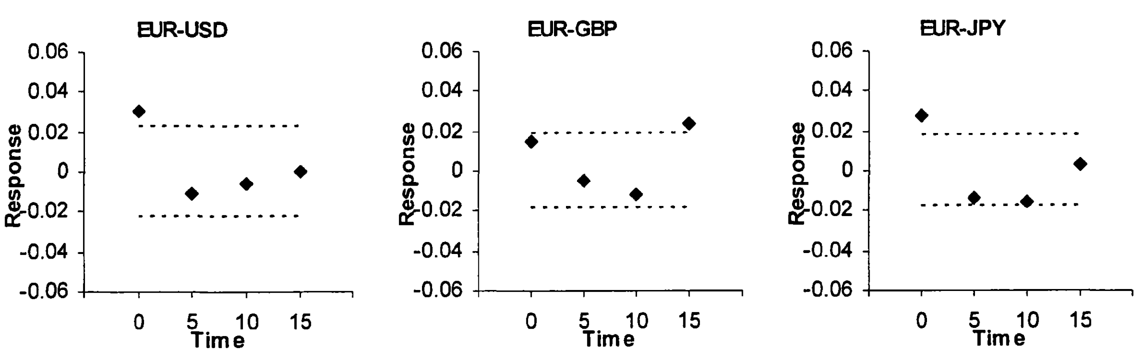
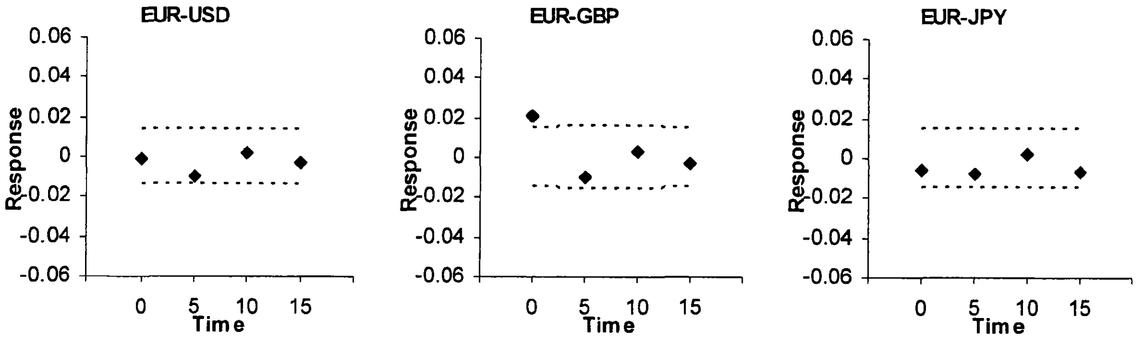
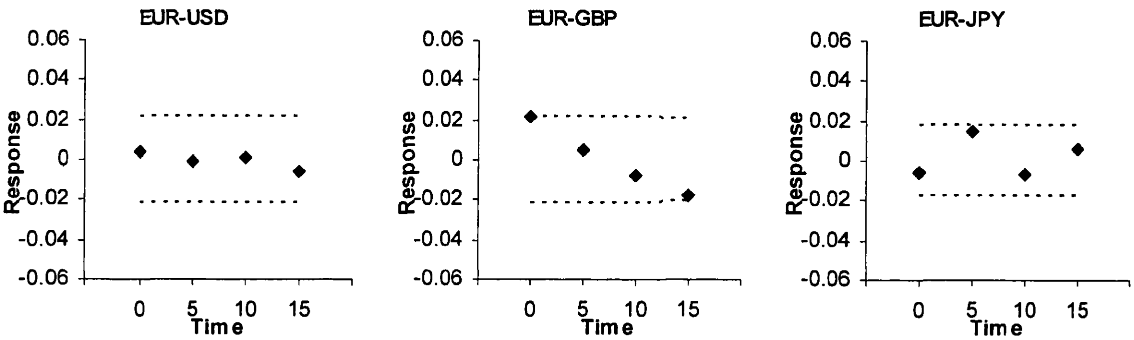


Figure 3.6.2.6. Dynamic Mean Response to French News.

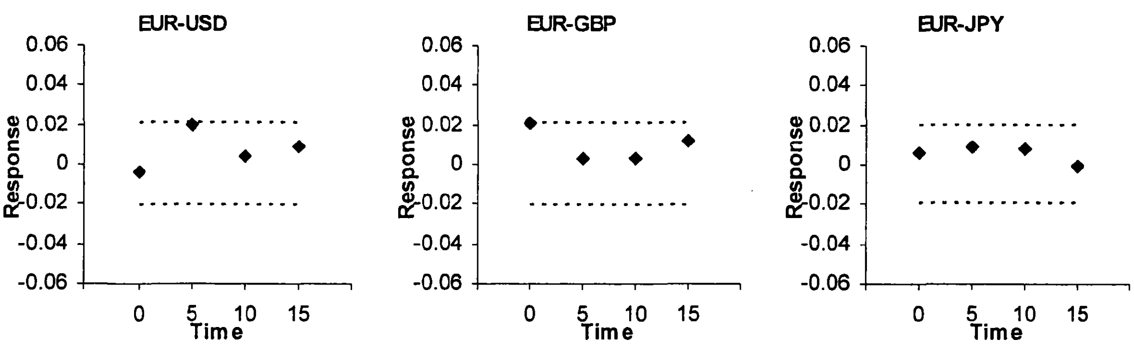
CPI Preliminary



PPI



Services Index



Trade Balance

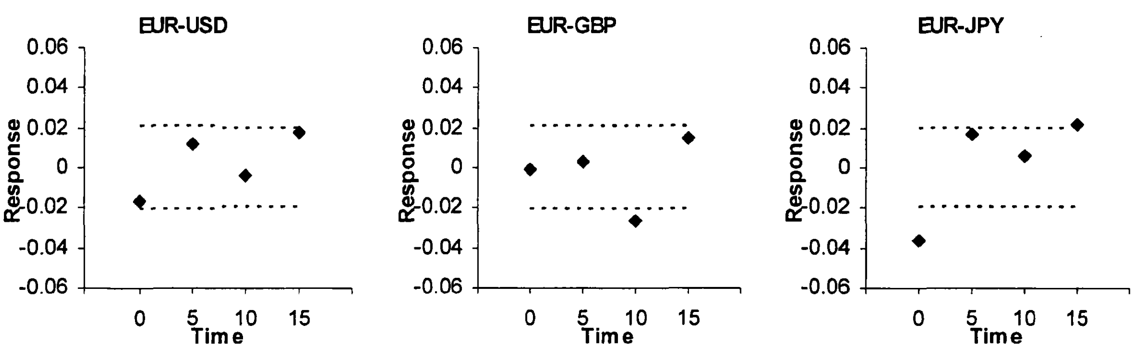
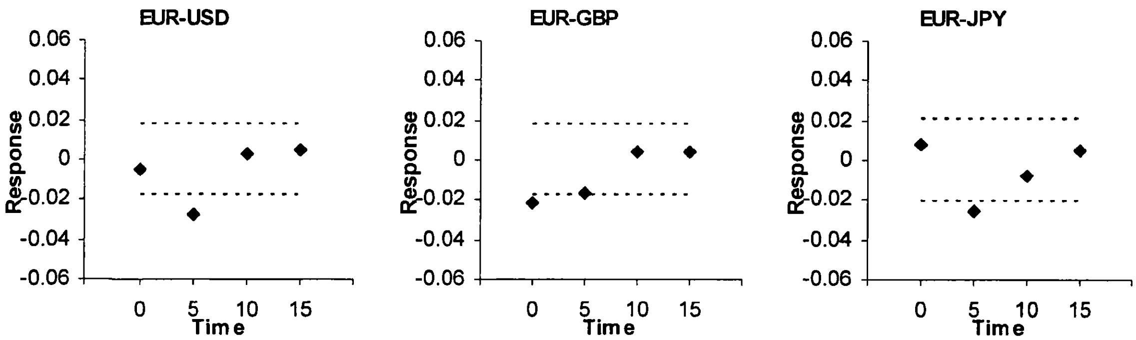
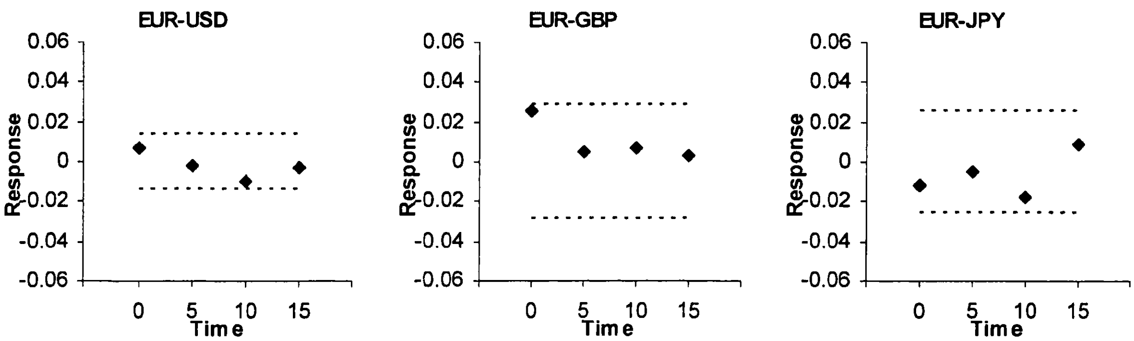


Figure 3.6.2.7. Dynamic Mean Response to UK News.

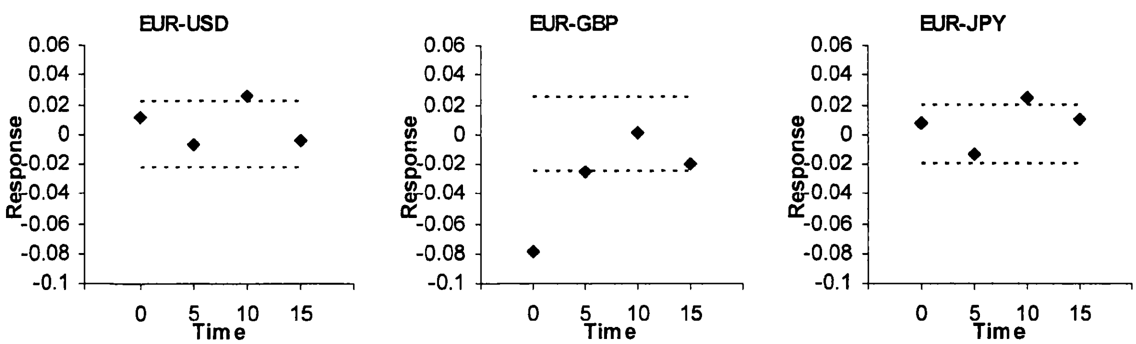
Balance of Payments (Trade)



GDP Final



Retail Sales



RPI

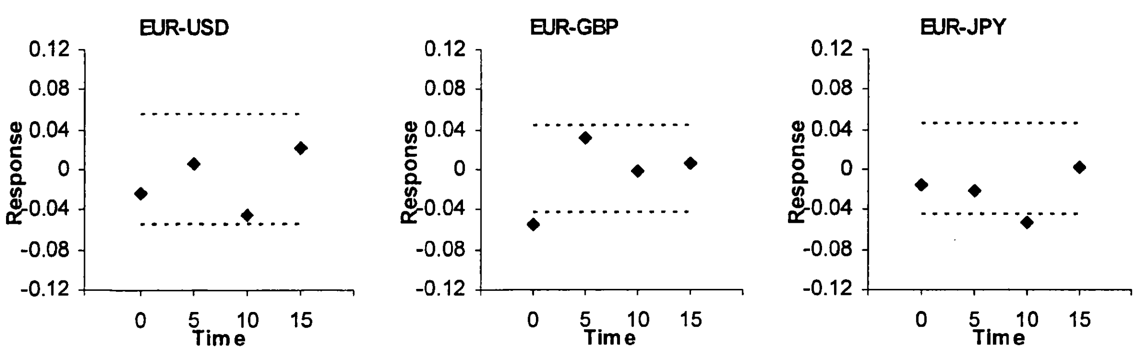
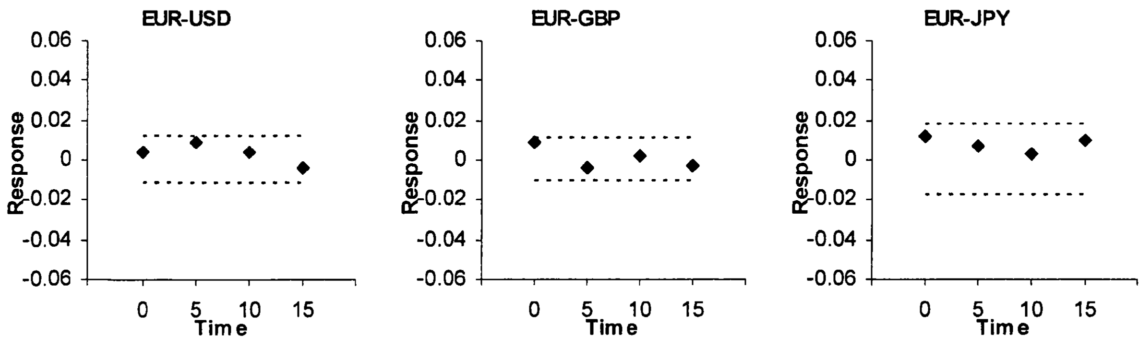
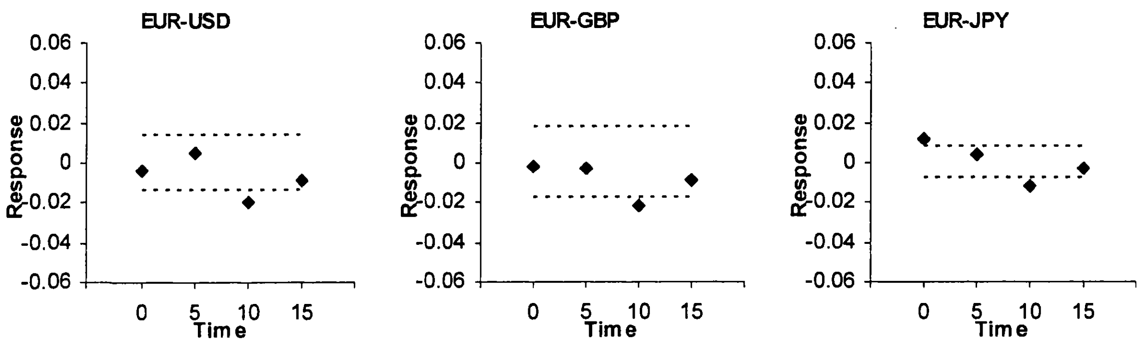


Figure 3.6.2.8. Dynamic Mean Response to Japanese News.

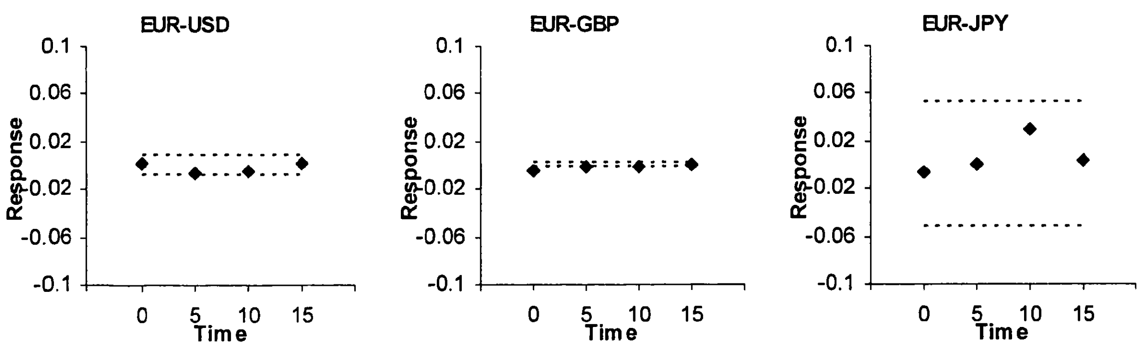
Housing Starts



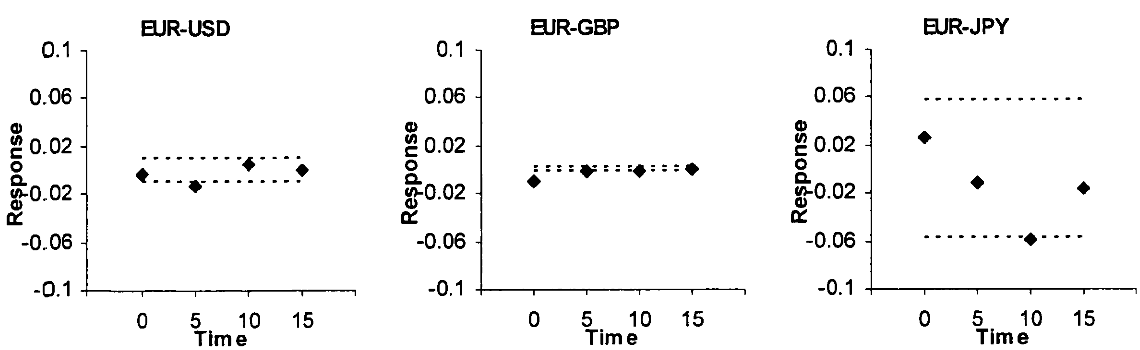
Industrial Production



Tankan Non Manufacturing



Tankan Manufacturing



3.6.3 Dynamic News Effects over Announcement Windows

In order to examine the dynamic effects of news in more depth, an alternative WLS version of equation (3.21) is estimated, which uses the three five-minute returns directly before and the eighteen five-minute returns directly following each announcement. The announcement window is therefore timed at fifteen minutes before and one and a half hours after each announcement in order to capture the systematic news responses in the mean, whilst modelling explicitly the volatility response depicted in section 3.3.7. As in the previous section, the conditional mean five-minute return during this announcement window is modelled as a linear function of I lags of returns with J lags of each of the K^c fundamentals for country c:

$$R_{t,n} = \beta_{0^c} + \sum_{i=1}^{I} \beta_{i^c} R_{t,n-i} + \sum_{k^c=1}^{K^c} \sum_{j=0}^{J} \beta_{k^c,j} S_{k^c,t,n-j} + \varepsilon_{c,t,n} . \tag{3.21}$$

Again the analysis is separated by country and given that the number of announcements varies for each country and that announcement windows occasionally overlap, the number of observations used in the estimation of equation (3.21) is 8,805, 4,601, 4,868, 3,934, 3,570 and 2,606 for the US, Eurozone, Germany, France, UK and Japan, respectively. $I=J=2$ is fixed uniformly across countries as indicated by the Akaike and Schwarz information criteria.

OLS estimation would produce consistent estimates for the coefficients of equation (3.21), but the evidence of section 3.3 confirms that the disturbance term for the five-minute return regressions will be heteroscedastic as it is influenced by the intraday volatility pattern. In order to enhance the efficiency of the estimates, a WLS procedure is applied involving two steps.[48] As previously, the first step estimates equation (3.21) for the announcement window by OLS. The second step uses the absolute value of the residuals to estimate a time varying volatility function, which is then used to perform a WLS estimation of (3.21). The temporal variation in five-minute return volatility around announcement times is modelled as:

[48] A simpler OLS estimation of (3.21) using heteroscedasticity and autocorrelation consistent standard errors was also performed. The WLS approach described in the text is preferred because of its direct handling of the known form of heteroscedasticity. The results of the two approaches are identical in qualitative terms.

$$\left|\varepsilon_{c,t,n}\right| = \sum_{i=1}^{I'} \beta_{c,i} \left|\varepsilon_{c,t,n-i}\right| + \sum_{\theta=1}^{\Theta} \xi_{c,\theta} D_{\theta} + \sum_{k^c=1}^{K^c} \sum_{j'=0}^{J'} \eta_{k^c j'} \left|S_{k^c t,n-j'}\right| + u_{c,t,n} \,. \qquad (3.23)$$

where $I'=9$ own lags of the absolute value of residuals capture ARCH effects and this number of lags is fixed uniformly across countries as suggested by the Akaike and Schwarz information criteria, and $\Theta=21$ such that the second summation term in equation (3.23) applies dummy variables to each of the five-minute intervals within the announcement window, and therefore capture the average volatility pattern around announcements. Since announcements in each country are generally made at the same time of day, this is tantamount to modelling the intraday volatility pattern that exists around announcements. The final term represents the absolute value of standardised news, measuring the information surprise element of announcements. $J'=1$ is fixed across countries, again as suggested by the Akaike and Schwarz information criteria.

Following the discussion in section 3.2.6, rather than list the full estimation outputs for each equation, the following analysis includes only the most important information describing the responses of the conditional mean exchange rate returns to macroeconomic announcements. First, Table 3.6.3.1 reports the statistically significant WLS instantaneous mean responses to news, $\hat{\beta}_{k^c,0}$, which confirms all previous findings in this section and are consistent with those reported by Andersen, Bollerslev, Diebold and Vega (2007). Standardised news on macroeconomic fundamentals exerts a very strong influence on the Euro exchange rate, in accordance with various exchange rate determination theories, in the five-minute interval in which the announcement was made. Throughout this chapter, the evidence suggests that news regarding US macroeconomic performance causes the most dramatic reactions in exchange rate returns and volatility and this is supported by the results shown in Table 3.6.3.1. In particular, US Consumer Confidence, GDP Advance, Non-Farm Payrolls, Retail Sales, Trade Balance and Initial Claims cause highly statistically significant and violent movements in the EUR-USD, EUR-GBP and EUR-JPY returns. In addition, Durable Goods Orders, Leading Indicators, Personal Consumption Expenditure and Productivity (Preliminary) also generate strong, statistically significant reactions in the EUR-USD plus one of the other rates investigated.

Table 3.6.3.1. Instantaneous Mean News Response from WLS Estimation for Announcement Window.

ANNOUNCEMENT	EUR-USD	EUR-GBP	EUR-JPY
US News			
Chicago PMI	**-0.0428***	-0.0078	-0.0142
Construction Spending	**-0.0569****	-0.0152	-0.0105
Consumer Confidence	**-0.1428****	**-0.0607****	**-0.0250***
Durable Goods Orders	**-0.0870****	**-0.0454****	-0.0230
GDP Advance	**-0.1759****	**-0.0893****	**-0.0848****
GDP Preliminary	**-0.0387+**	**-0.0297***	**-0.0380****
Leading Indicators	**-0.0403****	-0.0165	**-0.0303***
Non-Farm Payrolls	**-0.1677****	**-0.0556****	**-0.0295****
Personal Consumption Expenditure	**-0.0300****	-0.0032	**-0.0229***
Philadelphia Fed Index	**-0.0610****	**-0.0259****	-0.0230
Productivity Preliminary	**-0.0067***	**-0.0020****	-0.0044
Productivity Revised	0.0014	**0.0102****	0.0083
Retail Sales	**-0.1105****	**-0.0451***	**-0.0463****
Trade Balance	**-0.0831****	**-0.0433****	**-0.0341****
Unemployment Rate	**0.1169***	**0.0550+**	**0.0490+**
Initial Claims	**0.0374****	**0.0147***	**0.0115***
Federal Reserve FOMC	-0.0302	-0.0036	**-0.0142****
Eurozone News			
Business Climate Index	-0.0055	-0.0054	**-0.0138***
Current Account	-0.0228	-0.0139	**-0.0389****
GDP Revised	-0.0005	**-0.0104****	**-0.0084****
HCIP	**0.0061****	0.0066	0.0027
Labour Costs Revised	**0.0202****	**-0.0323****	**0.0216****
M3	**0.0111****	0.0084	**0.0169+**
German News			
Employment	0.0103	**-0.0022****	**-0.0300****
IFO Business Expectations	**0.0436***	0.0135	**0.0307***
Import Prices	**0.0016***	0.0120	0.0030
Cost Of Living Final	**-0.0148***	-0.0097	-0.0095
Services Index	**0.0275****	0.0065	**0.0195****
Unemployment	**-0.0192****	**-0.0146+**	**-0.0229+**
ZEW Expectations	**0.0419****	0.0183	**0.0304****
French News			
Business Climate	0.0003	**-0.0168***	**-0.0205****
CPI Preliminary	-0.0070	**0.0240****	**-0.0076****
Current Account	**-0.0106****	**0.0138****	-0.0095
GDP Final	**0.0157****	0.0018	-0.0078
Non-Farm Payrolls Preliminary	0.0142	**0.0124****	-0.0162
PPI	**-0.0358***	0.0192	-0.0004
PMI	0.0210	0.0073	**0.0212****
Trade Balance	0.0136	**0.0054****	-0.0167

Table 3.6.3.1. (Continued)

ANNOUNCEMENT	EUR-USD	EUR-GBP	EUR-JPY
UK News			
Balance of Trade	-0.0044	**-0.0183***	0.0101
Current Account	**-0.0096****	-0.0087	-0.0002
GDP Final	**0.0063***	**0.0184***	**-0.0128****
GDP Preliminary	-0.0113	**-0.0216****	**0.0157***
PPI Input	0.0096	**0.0122****	0.0064
PSNCR	**-0.0152***	0.0153	**0.0112+**
Retail Sales	**0.0134****	**-0.0799****	0.0069
RPI	0.0136	**-0.0520****	-0.0176
Unemployment	-0.0024	**0.0202***	**0.0204****
Japanese News			
Housing Starts	0.0006	**0.0050****	0.0101
Industrial Production	-0.0031	-0.0021	**0.0094****
Tankan Manufacturing	-0.0028	**-0.0141****	0.0158
Bank of Japan	**0.0045****	**0.0075****	**0.0096****

Notes: The table reports the instantaneous response to news announcements in the WLS estimation of equation (3.21) for the conditional exchange rate return, which uses only those observations falling in the announcement window fifteen minutes before and ninety minutes after announcements. Only those announcements producing at least one significant coefficient at the 5% level across exchange rates are included. **, * and + denote statistical significance at the 1, 5, and 10% levels respectively.

With regard to news emanating from other countries, Eurozone Labour Costs (Revised) remains an important release in this sample, as identified throughout this section, but it does not generate movements in the same direction consistently across all three exchange rates. Larger than expected increases in inflation (HCIP) and money supply (M3) cause a significant appreciation in EUR-USD and the reactions to these indicators are only significant in the analysis of announcement windows. GDP (Revised) is also important for the Eurozone, however, contrary to theory, faster than expected growth causes a weakening of EUR against GBP and JPY. For Germany, better than expected IFO Business Expectations, Services Index and ZEW Expectations lead to appreciation of EUR, whilst unanticipated increases in Unemployment provides a depreciation of EUR against USD.

Although increases in German Employment cause significant instantaneous responses in EUR-GBP and EUR-JPY, the coefficients are negative, indicating a depreciation of EUR relative to these currencies. The most important releases in France are the Business Climate Index, CPI (Preliminary) and Current Account, although the coefficients often have different signs for different currency pairs. Other notable French announcements are GDP (Final), Non-Farm Payrolls (Preliminary), PPI, PMI and Trade Balance, each having a statistically significant impact on returns for one of the currency pairs. UK news has a relatively stronger influence on EUR-GBP than the other currencies with better than expected GDP (Preliminary), PPI (Input) Retail Sales and RPI all showing coefficients significant at the 1% level, and there are notably more UK announcements that are statistically significant under this analysis of announcement windows. Finally, there are very few announcements from Japan causing significant instantaneous exchange rate movements. Those listed in Table 3.6.3.1 are the same as the important announcements identified in Tables 3.6.1.1 and 3.6.2.1 apart from the inclusion in this analysis of liquidity announcements from the Bank of Japan. The provision of more liquidity to the banking sector causes a significant appreciation of EUR across all three currency pairs. Somewhat surprisingly, however, unexpected increases in Industrial Production in Japan also give rise to a significant appreciation of EUR against JPY.

Figures 3.6.3.1 to 3.6.3.6 illustrate the dynamic response of exchange rate returns to news announcements for a selection of the most important announcements.

Figure 3.6.3.1. Dynamic Mean Response to US News for Announcement Window.

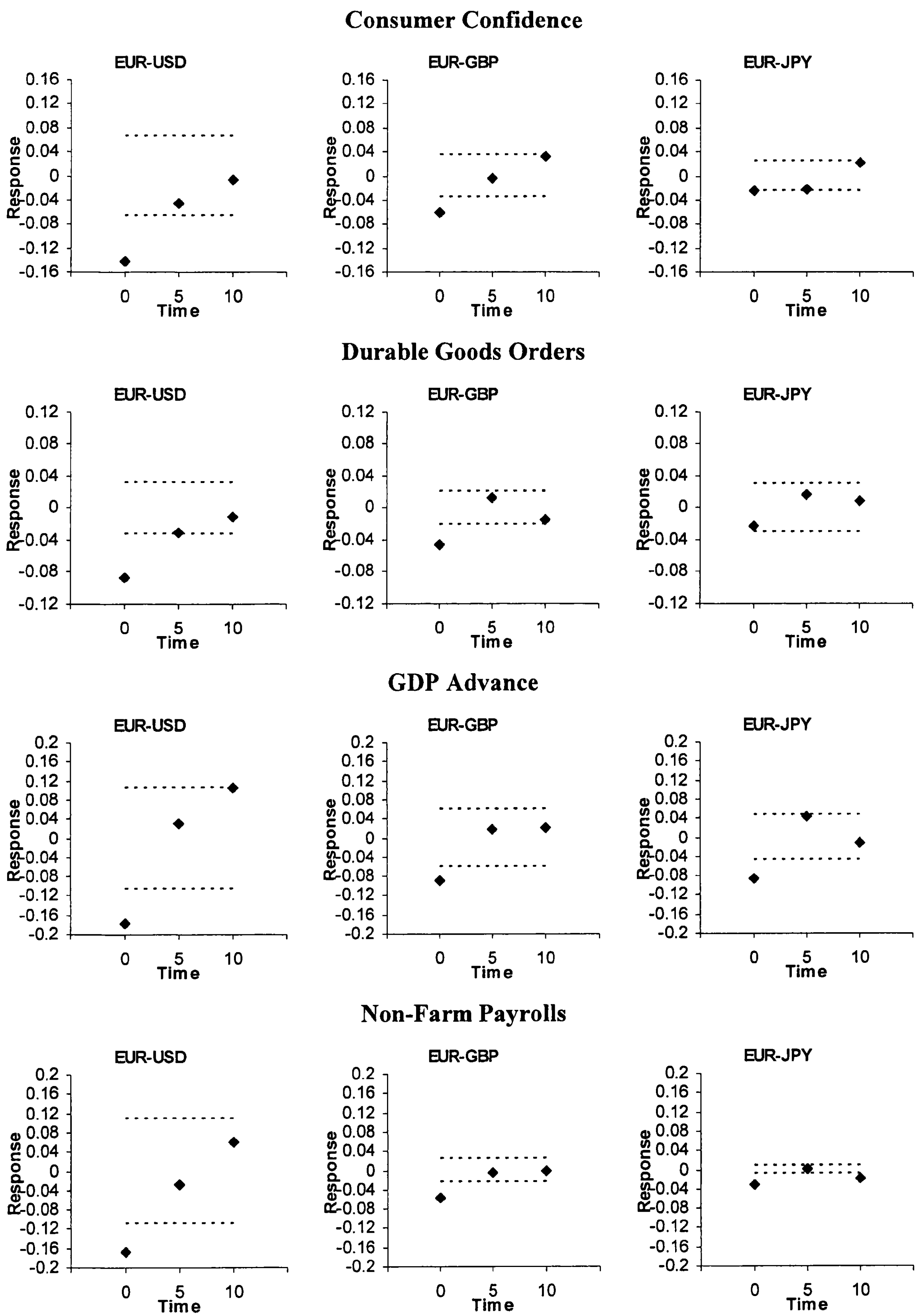
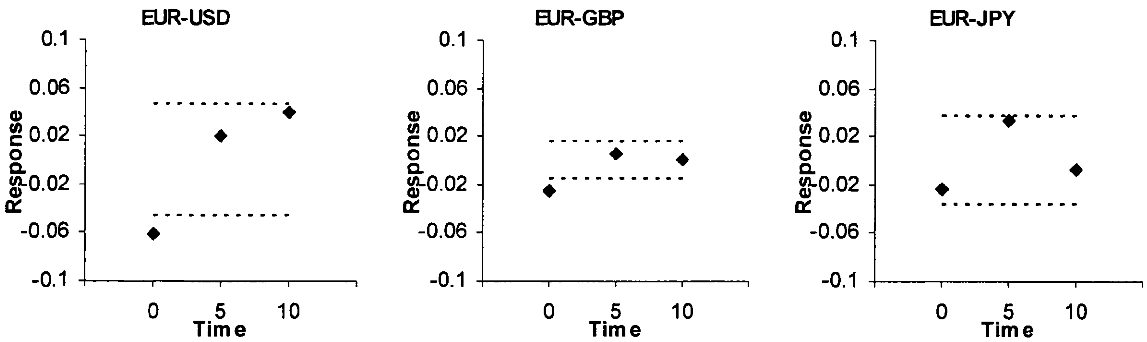
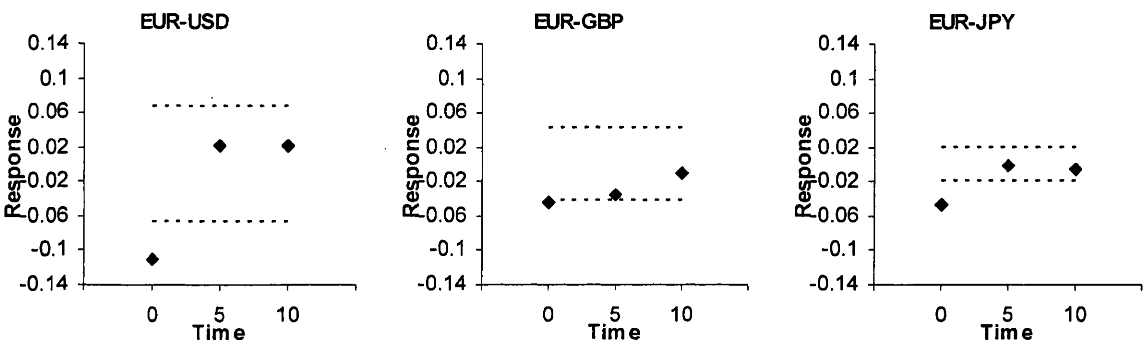


Figure 3.6.3.1. (Continued)

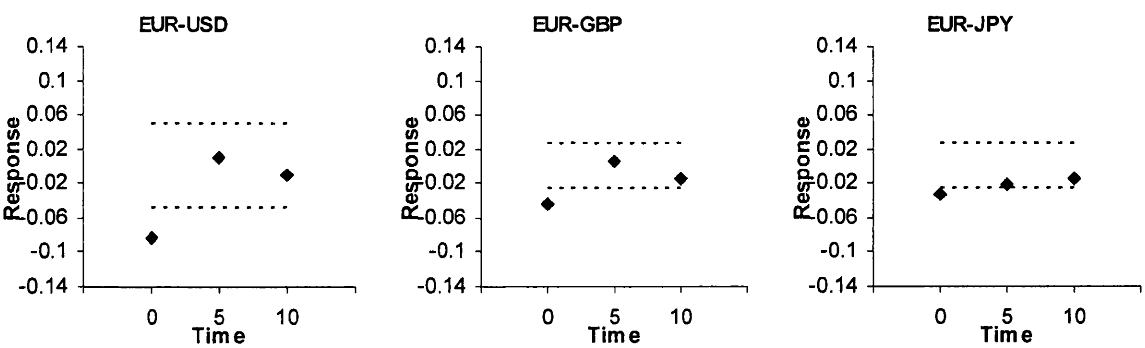
Philadelphia Federal Reserve Index



Retail Sales



Trade Balance



Unemployment Rate

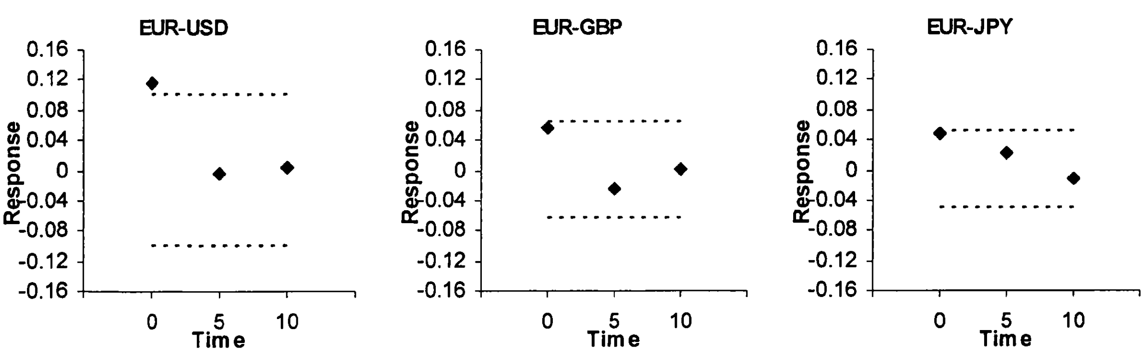
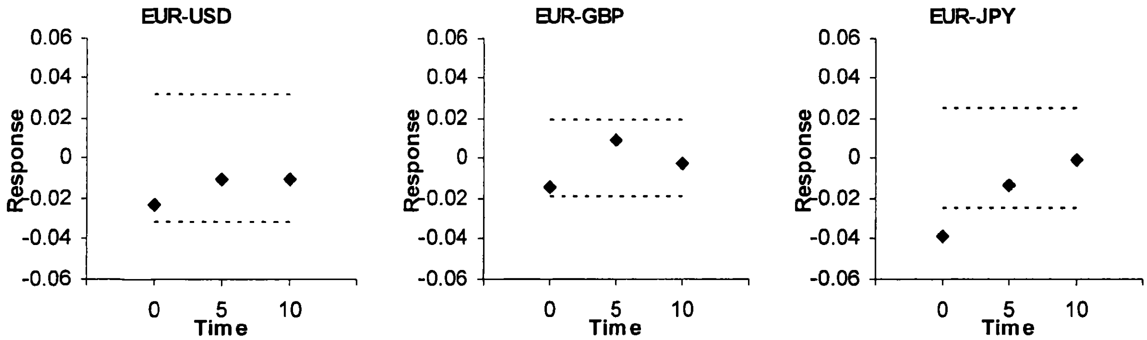
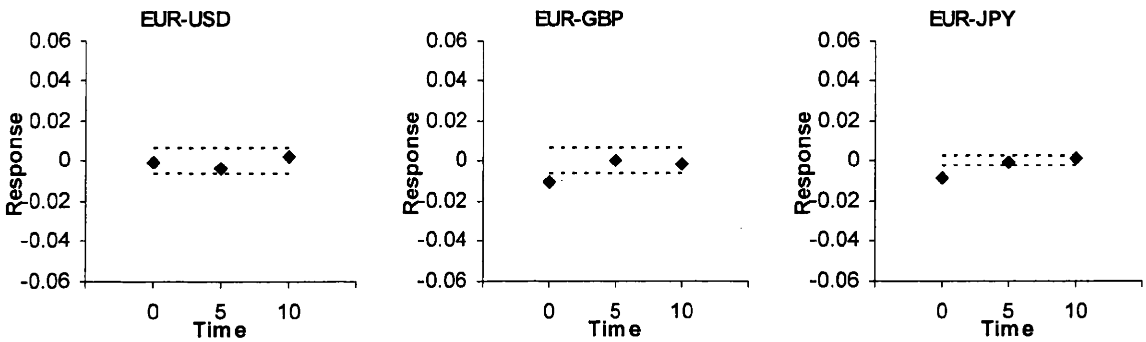


Figure 3.6.3.2. Dynamic Mean Response to Eurozone News for Announcement Window.

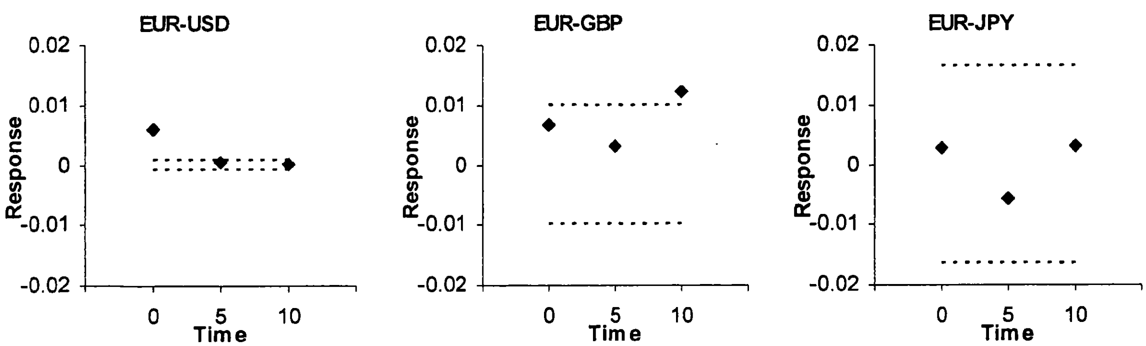
Current Account



GDP Revised



HCIP



Labour Costs Revised

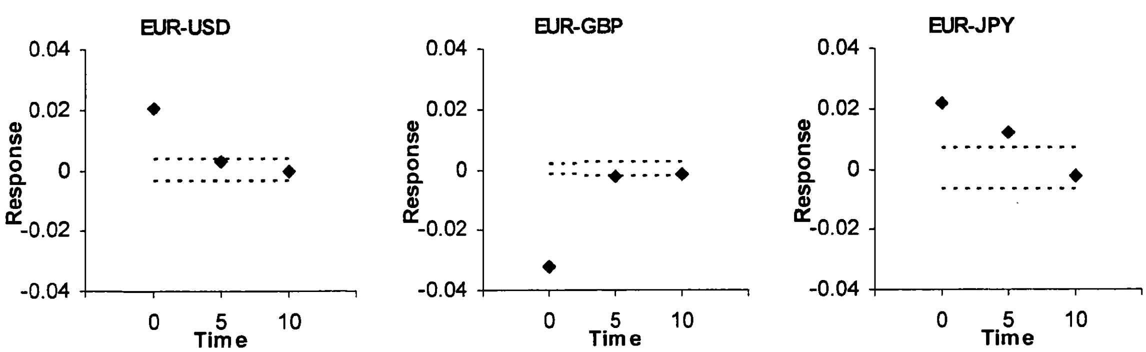


Figure 3.6.3.3. Dynamic Mean Response to German News for Announcement Window.

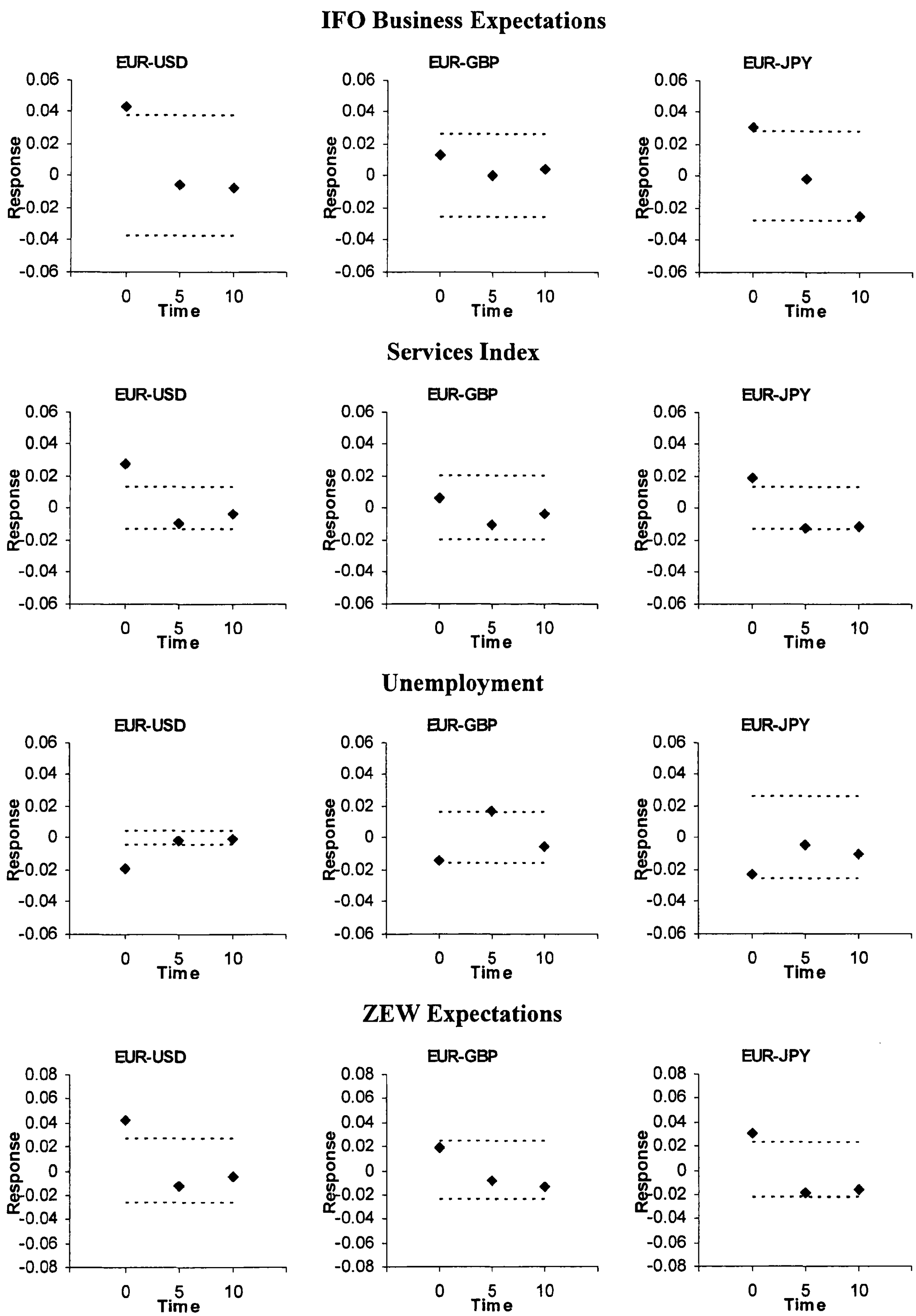


Figure 3.6.3.4. Dynamic Mean Response to French News for Announcement Window.

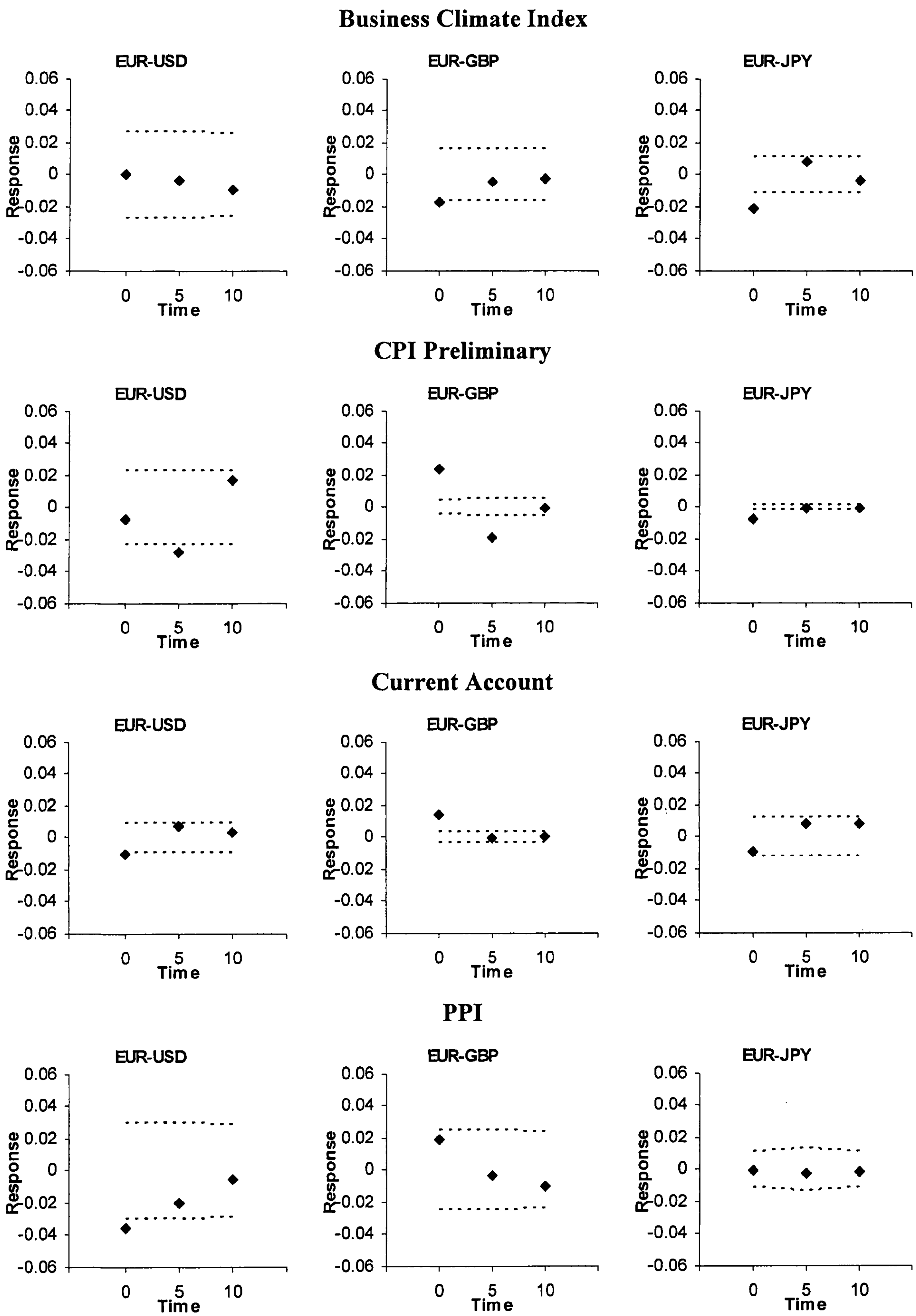
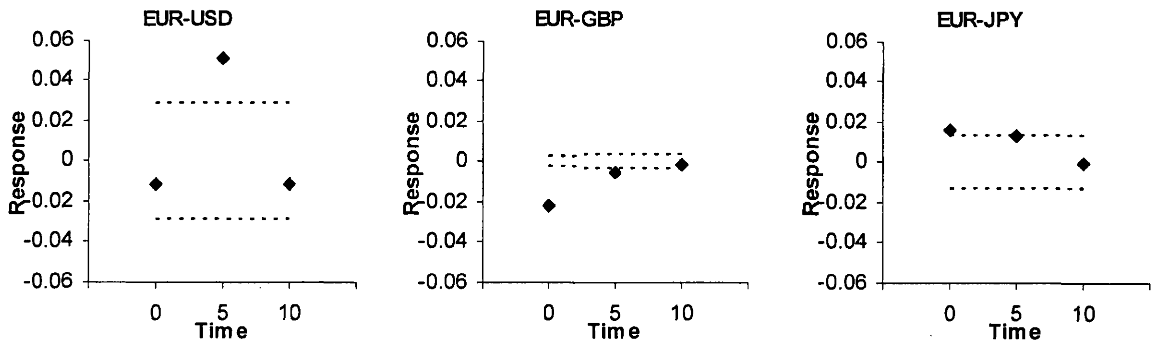
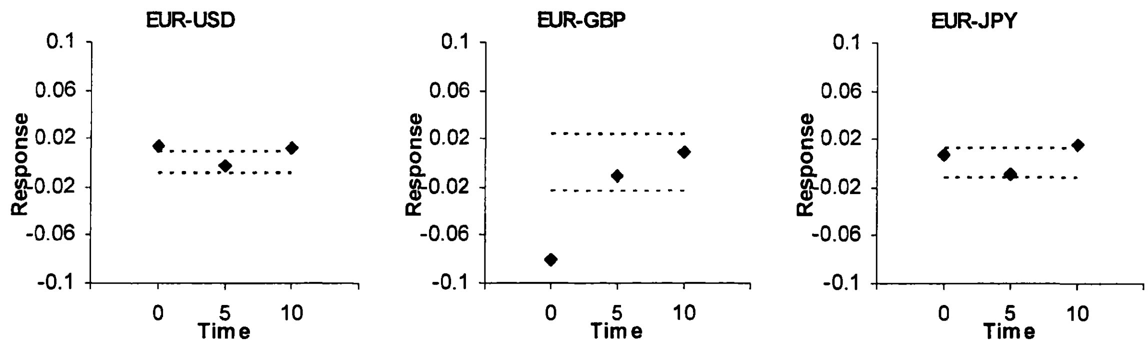


Figure 3.6.3.5. Dynamic Mean Response to UK News for Announcement Window.

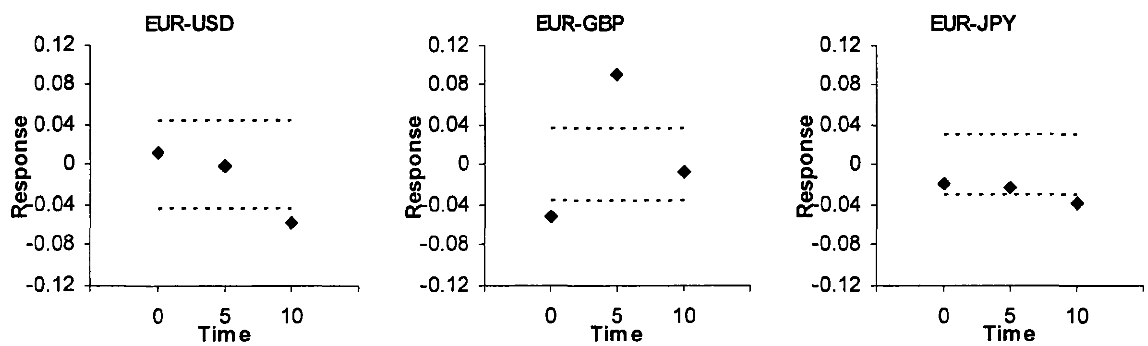
GDP Preliminary



Retail Sales



RPI



Unemployment

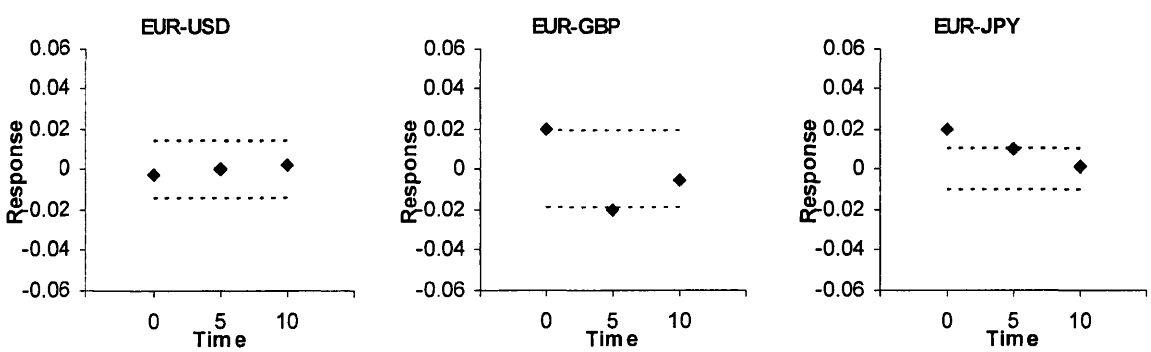
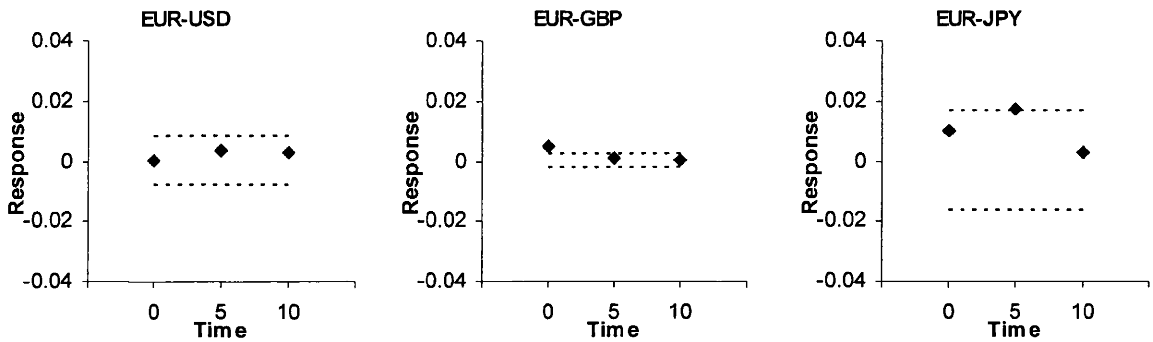
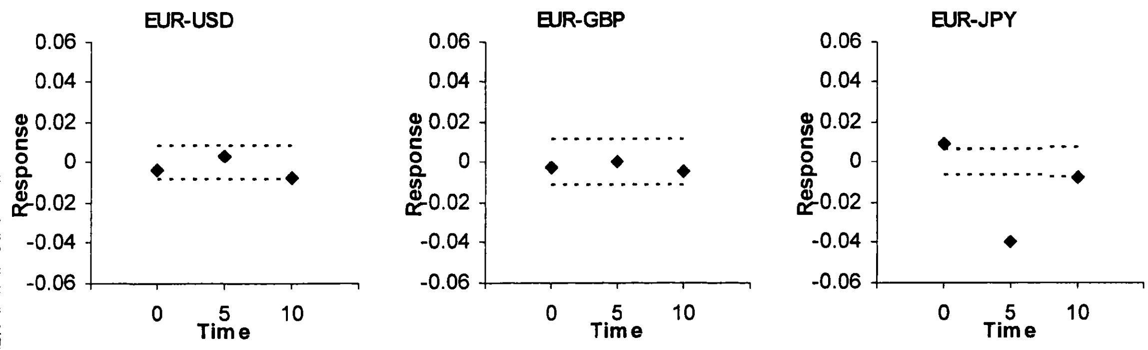


Figure 3.6.3.6. Dynamic Mean Response to Japanese News for Announcement Window.

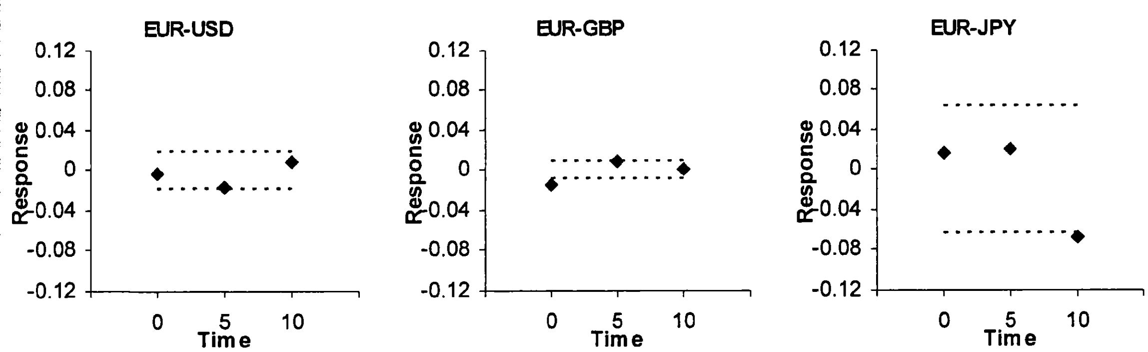
Housing Starts



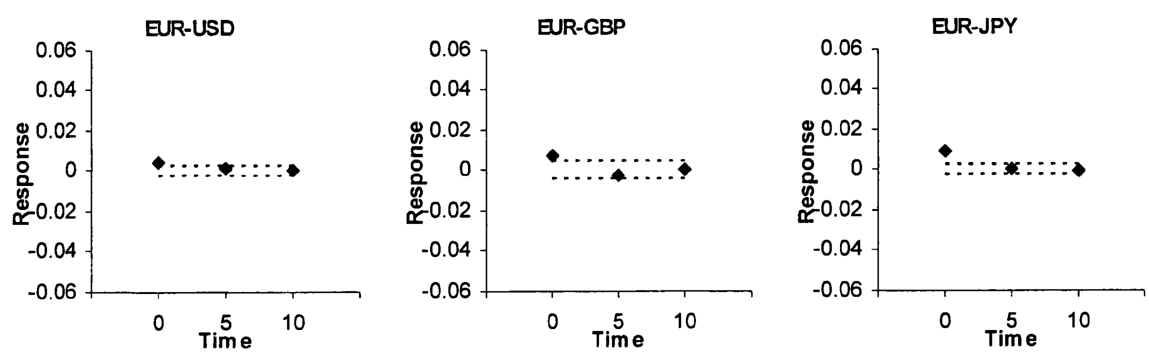
Industrial Production



Tankan Manufacturing



Bank of Japan



Coefficient values from the WLS estimation of equation (3.21) together with two standard error bands around the null hypothesis of zero response to news are displayed with announcements grouped by country. In support of the findings of the previous section, the reaction of exchange rates to macroeconomic news is very fast, the vast majority of the statistically significant adjustments occurring within five minutes of the announcement time, and little reaction thereafter, so characterising a jump in the conditional mean return. Reactions are far more dramatic in response to US macroeconomic news, and particularly for EUR-USD. During the five-minute interval occupying the data release, the EUR-USD exchange rate is linked closely to the news regarding underlying economic fundamentals with favourable US news associated with USD appreciation relative to EUR.

In concluding this section, it is important to emphasise the main findings from this analysis. US macroeconomic news generates far more dramatic responses in exchange rate returns and returns volatility than news on the macroeconomic performance of other countries. Eurozone, German, French and Japanese news have very little impact, though there is evidence that some UK announcements are important for the EUR-GBP rate. The reaction of exchange rate returns to news is very quick and occurs within the first five minutes of the release with very little reaction in the following fifteen minutes, thus enabling us to characterise such reactions as conditional mean return jumps. Initial volatility responses to macroeconomic news are equally dramatic, but these tend to linger for up to one hour after the release and in some cases for up to two hours. There are also some announcements that cause vigorous and persistent volatility reactions, but whose associated return response is not correlated to the standardised news measure of that indicator. Particularly noteworthy examples of this are interest rate decisions by the Federal Reserve, ECB and MPC and liquidity provision decisions by the Bank of Japan. Although these announcements cause the most volatile reaction of all the macroeconomic indicators, the conditional mean exchange rate return response is not systematically explained by the standardised measure of news used in this study. This may be because central bank announcements alone cause volatility quite apart from the information surprise. Finally, the evidence suggests that exchange rates, and the EUR-USD rate in particular, are strongly linked to macroeconomic fundamentals in the five-minute interval including the announcements. The conditional mean return jump reflects USD appreciation relative to EUR in response to unexpectedly strong US macroeconomic performance and when concentrating on the intervals containing announcements only, standardised news measures explain staggering proportions of these jumps.

3.7 CONCLUSION

The understanding, measurement and forecasting of financial market volatility form arguably the most important issues in financial economics and have received considerable research attention in recent decades. The characterisation of the price discovery process, and investigation of the way in which news about macroeconomic fundamentals is incorporated into asset prices, is also a central issue within the market efficiency and market microstructure theoretical literatures, but has so far enjoyed limited empirical success. In recent years, research focused on these core areas of finance has benefited greatly from the availability of high frequency financial data. This study has addressed these concepts jointly by investigating the short run reaction of exchange rate returns and returns volatility to macroeconomic news announcements.

It has been well documented that volatility is driven by three components: a distinctive, inherent intraday volatility pattern; macroeconomic news announcements; and a latent volatility factor often characterised by clustering and persistence at low frequencies. Using a nineteen-month sample of five-minute returns for three Euro exchange rates, and therefore a new market setting, this study confirms a twenty-four hour pattern for intraday volatility, with volatility rising at the opening and overlapping of trading activity in the world's major financial centres, and reports that the largest five-minute returns are found to coincide with the release of macroeconomic news. Rather than treating components in isolation, this study controls for each factor simultaneously in an attempt to isolate the response of volatility to macroeconomic news announcements. Whilst previous studies of this type filter intraday volatility by fitting a Fourier flexible form (FFF) to the intraday pattern, this study compares the performance of the FFF with an alternative cubic spline approach. Both specifications, in general, provide an excellent fit to the average intraday volatility pattern and capture the daily periodicity in the time series dependencies so as to highlight long memory as an inherent feature of high frequency returns volatility. Measurement of the response of volatility to macroeconomic news announcements, however, is sensitive to the econometric framework applied, with the FFF often understating their effects compared to the cubic splines.

The largest reactions of volatility across the three rates are found to occur in response to US news. In a period of poor global economic performance, the decisions of the FOMC regarding US interest rates generated the largest instantaneous jumps in volatility and often the largest cumulative response over the period immediately following the announcement. Interest rate decisions by the ECB also feature prominently showing that monetary policy decisions are an important source of exchange rate volatility over the sample, which may have been confounded during the sample period by the ECB's monetary policy reactions being difficult to predict accurately. In confirmation of previous studies, indicators of real activity such as the US Employment Report and GDP cause dramatic price reactions, whilst similar measures for the UK (including UK Industrial Production), Eurozone, Germany and Japan are among the highest ranking non-US announcements. The US Trade Balance is also found to be important, causing a larger reaction than US inflation data. Aside from such traditional macroeconomic information, forward looking indicators and regional economic surveys are found to play a crucial and interesting role. These releases include the Philadelphia Federal Reserve Index, University of Michigan Consumer Sentiment Index, Chicago Purchasing Managers Index, Consumer Confidence Index and Institute of Supply Management Index for the US, and the IFO Business Expectations Index for Germany. Their release timing is such that they are the first indicators of macroeconomic performance for a particular month that traders observe, and 'data surprises' are likely to generate larger price reactions. By learning from this early information, subsequent announcements pertaining to the same month can be forecast with greater accuracy, such that deviations from expectations are small and hence do not cause such dramatic volatility movements.

The components of high frequency returns volatility are not only significant and interesting in statistical and economic terms, but the identification and accurate modelling of their dynamics are also crucial in order to conduct a robust investigation of the response of returns to news announcements. Under this methodology exchange rates are found to react very quickly to macroeconomic surprises, specifically, within five minutes of the release. With very little reaction thereafter, the immediate behaviour of returns can be described as conditional mean jumps. Furthermore, within this five-minute interval containing the announcement, macroeconomic innovations explain large proportions of the jumps. The largest jumps follow US news with unexpected strengthening of the US economy causing the Euro to depreciate and against the US Dollar in particular. Construction Spending, Consumer Confidence, Durable Goods Orders, GDP Advance, GDP Preliminary, ISM Index (Manufacturing), Leading Indicators, Non-Farm Payrolls, Philadelphia Federal Reserve Index, Retail Sales, Trade Balance, Unemployment Rate and Initial Claims are all important announcements form the US, whilst Labour Costs Revised for the Eurozone, IFO Business Expectations and ZEW Expectations for Germany, and Trade Balance, GDP Preliminary, Industrial Production, Manufacturing Output, Retail Sales, RPI and RPIX for the UK are the non-US announcements influencing exchange rate returns. Interestingly, despite causing large responses in returns volatility, the large jumps in returns following interest rate decisions do not appear to be correlated with the informational innovation surrounding their announcement.

The sample used in this study is particularly interesting as it covers a period of economic turbulence, geopolitical tension and episodes of monetary policy easing. However, it would be interesting to extend the sample to cover different phases of the business cycle in order to analyse whether markets react symmetrically to good and bad news and whether this reaction is symmetric during economic expansions and contractions. Given the importance of monetary policy reactions identified in this study, it would be particularly interesting to relate possible asymmetric news effects to the reaction functions of monetary policy authorities. Finally, in the context of realised volatility models, the econometrics of detecting, quantifying and explaining volatility 'jumps' is an innovative area of empirical finance and such 'jump' contributions to total volatility are, obviously, likely to be linked to macroeconomic news announcements.

CHAPTER 4

JUMP VARIATION, INTRADAY JUMPS AND MACROECONOMIC NEWS ANNOUNCEMENTS

ABSTRACT

This chapter investigates the empirical performance of non-parametric jump detection procedures and the relationship between US macroeconomic news announcements and intraday jumps for nine futures markets, including foreign exchange, equity index and interest rate futures for the US, UK and Europe. Based on the foundation of a jump-diffusion log-price process, non-parametric techniques are applied to high frequency returns data to separate the continuous sample path and jump components of the quadratic variation of the price process. At the daily level, jumps occur far more frequently than would be expected from a continuous sample path diffusion process and jumps tend to be large, contribute heavily to total variation and exhibit dynamic dependence, suggesting predictability. Intraday jumps are associated with extreme five-minute returns, which contribute substantive proportions to realised variation, and these results are robust to the annihilation of the inherent intraday volatility patterns and alternative intraday jump detection procedures. Large proportions of jumps are caused by the release of macroeconomic news and jumps are significantly larger when coinciding with news releases, showing pure announcement effects. In addition, intraday jumps that are caused by announcements of Consumer Confidence, GDP Advance, Initial Claims, ISM Index, Retail Sales, Trade Balance, and especially Non-Farm Payrolls are significantly related to the information surprise, with innovations explaining staggering proportions of these intraday jumps. These findings demonstrate the importance of jumps and confirm the economic significance of the relationships between instantaneous jumps and news relating to economic fundamentals.

4.1 INTRODUCTION

The distributional properties of daily or lower frequency asset prices and the dynamics of asset price volatility have been the most widely studied topics in financial economics recently, with important implications for the risk-return tradeoff and asset pricing, portfolio allocation, risk management techniques and derivative pricing. One stylised fact emerging from empirical studies reveals that discretely sampled asset prices exhibit extreme violent movements, or outliers, so that their unconditional returns distributions have 'fat tails' relative to the Gaussian distribution. Attempts to explain this behaviour have included the Mixture-of-Distributions (MDH) of Clarke (1973), which, following a Central Limit Theorem argument, suggests that daily returns represent a mixture of normals distribution derived from a large number of intraday price movements. Since these intraday returns are governed by the arrival of new information, which is independent and identically distributed across these intraday returns, the extent of the deviation from normality at the daily level is driven by the distribution of this news arrival, or mixing variable. Whilst trading volume has been implemented as an observable economic version of the mixing variable (Epps and Epps, 1976 and Tauchen and Pitts, 1983), treating this as latent has spurred the vast literature on stochastic volatility, formalised initially by Taylor (1986), which accounts for much of the dynamics of short term asset returns.

Meanwhile, the empirical regularities surrounding the volatility of discretely sampled asset returns are temporal dependence, persistence, clustering and a volatility feedback (or leverage) effect. These features are addressed in the expansive (G)ARCH class of models, initiated by Engle (1982) and Bollerslev (1986), which provide arguably the most popular method of empirically characterising discrete time return distributions, and have provided the cornerstone for an enormous empirical and theoretical literature. Despite these advances in understanding of the distributional properties of daily returns, it is widely recognised that the most important developments in theoretical asset pricing have been based on continuous-time methods. Early studies aimed to provide continuous-time models that were more realistic in explaining these salient characteristics of return distributions. Specifically, Merton (1976) advocated the need to explicitly incorporate discontinuities, or jumps, into the price process, whilst Hull and White (1987) highlighted the importance of including time varying diffusive volatility. More recent advances demonstrate the need to incorporate both factors to improve empirical performance, suggesting that price processes are best described by jump-diffusion models comprising a smooth, slowly mean reverting continuous sample path and a less persistent jump component.

Another important, recent innovation in financial econometrics has been the availability and application of high frequency asset price data. Aside from investigating the intraday behaviour of returns and volatility, which are interesting in their own right, this development has sparked a rapid growth in the non-parametric literature which harnesses the tremendously useful information contained in high frequency returns in order to measure realised volatility at the daily frequency more accurately. In the framework of arbitrage free continuous-time jump-diffusion models, realised volatility is found to provide a consistent estimate of the quadratic variation of the prices process, which includes the variation due to jumps. In the very latest developments, Barndorff-Nielsen and Shephard (2004b, 2006) provide a non-parametric measure of realised bipower variation, which is a consistent estimator of the continuous sample path, thereby isolating this component of quadratic variation. The importance of this result is that the difference between empirical measurements of realised variation and bipower variation provides a consistent estimate of the jump variation. Since this detection procedure is limited to the daily level, it is unable to separate multiple jumps on particular trading day, and so the method has been focussed on improving our understanding of asset price dynamics and volatility at the daily frequency. However, the very recent work of Andersen, Bollerslev and Dobrev (2007) and Andersen, Bollerslev, Frederiksen and Nielsen (2006) extends this notion to allow the possibility of multiple intraday jumps and the identification of their exact timing. This is important in their studies for adjusting high frequency returns series for these jumps, to eliminate the impact of outliers, before transforming this jump-adjusted series into 'financial' time, to annihilate the volatility feedback effect, before confirming that the distributional properties of appropriately adjusted returns are Gaussian.

In addition to the study of volatility, high frequency data has allowed deeper investigation of market microstructure and market efficiency, including the short term reaction of asset prices to information arrivals. Perhaps the most interesting of these themes examines the reaction of returns and volatility to US macroeconomic news announcements, thereby assessing the relationship between financial markets and economic fundamentals. The evidence of the previous chapter supports the findings of Andersen, Bollerslev, Diebold and Vega (2003, 2007), among others, that asset prices react violently in the five-minute intervals immediately following the release of unexpected macroeconomic data. Whilst the studies of Barndorff-Nielsen and Shephard (2006) and Andersen, Bollerslev and Diebold (2007b) suggest links between macroeconomic news announcements and daily jump variation measures, and Andersen, Bollerslev and Dobrev (2007) and Andersen, Bollerslev, Frederiksen and Nielsen (2006) implement intraday jump detection procedures, a detailed investigation of the association of macroeconomic innovations and jumps has yet to be undertaken.

This chapter, therefore, aims to combine several strands of the recent asset pricing and financial econometrics literatures. The theoretical framework is built on the foundation of an arbitrage free jump-diffusion continuous-time model. In this context, and implementing high frequency data across an extensive range of international futures markets, this work adopts alternative non-parametric jump identification procedures to investigate the relative importance of jump intensity and magnitude as a component of total price variation. Furthermore, this study implements a range of intraday jump detection techniques to locate the precise timing of jumps and assesses the extent to which both pure announcements and the informational surprise delivered by those announcements can cause jumps and explain their magnitude. The results, consistent across geographic locations and asset classes, show that jumps are an integral part of the price process, confirming the findings of the existing literature. That is, there are far more jumps detected than would be expected from a purely continuous sample path process and the jumps contribute a significant proportion to total price variation. At the intraday level, jumps are very strongly related to macroeconomic news announcements. Macroeconomic news announcements explain large proportions of these jumps, and the absolute size of intraday jumps that are caused by news is dramatically larger than those not related to news, and by statistically and economically significant amounts. Additionally, jumps are statistically and economically significantly related to the information surprise of the announcements, with standardised news measures explaining striking proportions of the jumps, showing dramatic and systematic influences of the news on jumps. These findings, therefore, provide new evidence demonstrating the importance of jumps for the price process, across a range of alternative test statistics and futures markets. These results thus provide new evidence relating to the instantaneous response of asset prices to news regarding macroeconomic fundamentals, showing the dramatic influence of news in causing and explaining jumps and, are the first to illustrate the economic causes of jumps.

The remainder of the chapter is organised as follows. Section 4.2 provides an extensive review of the important recent contributions in the literature before section 4.3 explains the theoretical background and econometric method employed in detecting jumps. The data and results for daily jumps are explained and discussed in section 4.4 and the relationships between macroeconomic news and intraday jumps are investigated and analysed in section 4.5. Section 4.6 concludes the chapter and suggests possible avenues of further research.

4.2 LITERATURE REVIEW

Continuous-time diffusion processes have formed the basis for theoretical asset and derivative pricing models for many years. However, the development of empirical procedures for the estimation and inference of such continuous-time models has been hindered due to their incompatibility with the discrete nature of asset price data. More recently, research activity has made significant progress along two fronts in this context using parametric and non-parametric techniques. For the continuous-time parametric models, research has focused on the development of various estimation techniques in order to assess the relative empirical success of numerous realistic candidate models for asset prices. In particular, recent evidence across financial markets reveals overwhelming evidence for the presence of discontinuities or jumps in the price process. In parallel, non-parametric techniques have concentrated on utilising the considerable information held in high frequency asset returns to measure the quadratic variation of the price process. In the most innovative recent work, the quadratic variation process of continuous-time semi-martingale processes has been separated into a continuous component and a jump component, offering a model free and computationally simple procedure for identifying and measuring asset price jumps. This decomposition offers important gains towards the accuracy of measuring, modelling and forecasting asset return volatility and has allowed the distributional properties, intensity, and contribution to total price variation of jumps to be analysed. Some tentative suggestions and preliminary case studies have linked jumps to the arrival of news, but a formal examination of these relationships has yet to be conducted. The following review documents these important recent developments in the financial econometrics literature and places the contribution of this chapter, the rigorous investigation of the economic relationships between jumps and news, at the forefront of this field.

4.2.1 Parametric Models and the Importance of Jumps

As noted by Andersen, Bollerslev, Frederiksen and Nielsen (2006), some of the most important developments in theoretical asset pricing, and derivatives pricing in particular, have been based on continuous-time methods and models. But, since we do not observe continuous sample paths for asset prices in practise, empirical work assessing the performance of realistic continuous-time asset price processes, which relies on discretely observed data, has been hindered. Advances in research activity recently, however, has allowed important headway to be made and this sub-section reviews the developments that are of particular relevance to this chapter.

The simplest possible continuous-time model is provided by the time-invariant diffusion, which underlies the famous Black-Scholes option pricing formula. With a deterministic mean and constant volatility, the model can be estimated easily from discrete data, but its empirical performance is found to be very poor due to its inability to accommodate the strong temporal dependence exhibited in volatility. As a result, more complicated structures, such as the Ornstein-Uhlenbeck (OU), Constant Elasticity of Variance (CEV), and the square root or Cox, Ingersoll and Ross (1985) (CIR), processes have been developed to incorporate mean reversion and a well behaved diffusive volatility process. Although relatively easy to estimate through maximum likelihood techniques, these one-factor models falter dramatically when applied to actual asset price data. In search of more satisfactory empirical performance, research has progressed towards multi-factor parametric formulations, which allow the volatility process itself to be random, known as continuous-time stochastic volatility models. A particularly influential specification has been the square-root volatility model attributed to Heston (1993). One major advantage of a two-factor model is that the standard Brownian motion processes driving volatility and returns may be correlated, introducing the possibility of an asymmetric return-volatility relation, known as a leverage or volatility feedback, into the asset price dynamics.

The stochastic volatility diffusions are much harder to estimate from discretely observed data than the classical one-factor models. Two particular problems that arise are that volatility is latent and so any estimation procedure must use an imperfect proxy for volatility, and, even if the volatility process were observable at discrete points in time, closed form solutions may not be available for many of the continuous-time models employed in the literature. However, recent progress in the literature has proposed numerous estimation strategies to deal with these complications. The most important contributions are the quasi-maximum likelihood (QML) estimator of Ruiz (1994) and Harvey and Shephard (1994); the Markov Chain Monte Carlo (MCMC) methods of Jacquier et al. (1994), Eraker (2001, 2004), and Eraker et al. (2003); and the Efficient Method of Moments (EMM) estimation developed by Gallant and Tauchen (1996).[1] The empirical evidence suggests that these models provide major improvements over the traditional one-factor models, although they struggle to explain equity and interest rate data sufficiently accurately. For example, Andersen and Lund (1997) implement the EMM procedure to provide consistent estimates for the parameters of a two-factor continuous-time model for the short term risk-free rate. They show that the incorporation of the stochastic volatility factor greatly enhances the model's ability to fit the data, thereby extending the one-factor CIR model to a stochastic volatility setting, but that it remains difficult to replicate the fat-tailed innovations of the conditional distribution. Further support for the inclusion of a second stochastic volatility factor is provided by Andersen, Benzoni and Lund (2002), who investigate the relative success of numerous possible candidate continuous-time models to explain equity returns. Whilst they find that the stochastic volatility factor is an essential element of the model, two-factor models remain unable to replicate certain features of returns distributions. In particular, two factor models are rejected in favour of those that include both discrete jump components to accommodate the fat tails of the return distributions, and a negative correlation between return and volatility innovations to capture the skewness of S&P 500 returns.

The inability of pure diffusion processes to explain the fat-tailed property of asset returns, together with the compelling empirical evidence for the presence of asset price jumps, particularly in response to macroeconomic news and earnings

[1] Other notable works include Aït-Sahalia (2002), Bollerslev and Zhou (2002), Chernov et al. (2003), Duffie et al. (2000) and Pan (2002).

announcements, has prompted the inclusion of a jump component as an essential factor in continuous-time models. The improvement in the empirical performance of continuous-time parametric models, along with the detection of jumps and the evaluation of their economic importance and contribution, has spurred a burst of recent research activity in which jumps are the object of intrinsic interest. The basic building block for pure jump martingales is the standard Poisson jump process, which has a long history in financial economics (Merton, 1976), and a number of recent studies have demonstrated the need to allow for such a process in addition to a time-varying diffusive volatility component in order to represent observed price processes satisfactorily.

In an early study documenting the presence of jumps, Jorion (1988) finds that exchange rates exhibit systematic discontinuities, with this jump component explaining some of the empirically observed mis-pricings in the currency options market. Indeed, the implied volatility literature, and the investigation of 'volatility smiles' and 'smirks' in particular, seems to have evidenced the importance of incorporating jump processes slightly earlier than empirical work on other financial assets. Specifically, the contributions of Bates (1996, 2000) and Bakshi et al. (1997) reveal strong discrepancies between the characteristics of the return dynamics implied by options prices and those inferred from the actual time series of options prices. Stochastic volatility models based on implied data require extreme parameters that are at odds with the time series properties of actual options prices. Including a jump component in addition to stochastic volatility is found to provide a better fit for option prices. However, this addition is still unable to explain the high 'volatility of volatility' implied by options prices, prompting suggestions that 'jump fears' (Bates, 1996, 2000) or 'jump risk premia' (Pan, 2002) are important in reconciling this and in explaining volatility smiles and smirks.

The bulk of the more recent empirical work has concentrated on equity indices and interest rates. For example, the influential work of Andersen, Benzoni and Lund (2002) was one of the earliest empirical investigations of continuous-time equity return models, demonstrating that any reasonably descriptive continuous-time model for equity index returns must allow for discrete jumps as well as stochastic volatility, and a pronounced negative relationship between return and volatility innovations. Using daily observations of the broad S&P 500 index and its highly liquid options contracts in order to capture high frequency fluctuations in returns that are critical for identifying jump components, results indicate that both stochastic volatility and discrete jump components are critical ingredients for modelling returns. A low-frequency jump component, with jumps estimated to occur on average three or four times a year, accounts for the fat tails of the return distribution and most jumps are found to occur within a three percent band above and below zero. In reference to the options market, Andersen, Benzoni and Lund (2002) show that the jump component helps to induce a smirk in the implied volatility pattern, which mimics the pattern extracted from options data, revealing a general correspondence between the dominant features of the equity index returns and options prices.

Recognising the inability of simple, one-factor, stochastic volatility models to match the high conditional kurtosis of returns, Chernov et al. (2003) evaluate the role of additional volatility factors and jumps in the appropriate modelling of equity returns. In the estimation of ten models using a long sample of daily observations on the Dow Jones Industrial Average (DJIA), results show that none of the one-factor stochastic volatility models fit the data well, which confirms previous findings. Two-factor models, where one factor accounts for the persistence in volatility and the second determines the tail behaviour, offer empirical improvements and, importantly, the data reveal that abrupt changes in volatility are an essential ingredient to the success of the model with simultaneous jumps in returns and volatility appearing to offer an improved framework. Continuous-time stochastic volatility models incorporating jumps in returns and volatility are also investigated in Eraker et al. (2003) in an attempt to rectify the inability of jump-diffusion models to emulate the abrupt increases in volatility evident in the empirical literature. In investigation the S&P 500 and Nasdaq 100 index returns, the contribution of their study extends beyond the estimation of parameters and model performance evaluation to focus on jumps as the object of intrinsic interest by estimating jump times, jump sizes, and the contribution of jumps during periods of market stress. Eraker et al. (2003) find strong evidence for the presence of jumps in both volatility and returns and suggest that models without jumps in volatility are mis-specified. Jumps in returns are found to occur only once or twice per year, but, typically, the jumps are large and explain between eight and fifteen percent of the total variance of returns. Jumps in volatility are also important as they allow volatility to increase rapidly, particularly in periods of market stress, and little mis-specification is found for models including such jumps in volatility. Eraker (2004) corroborates this evidence, showing that a volatility jumping model improves markedly on simpler models.

Empirical evidence from the analysis of interest rates supports the presence of discontinuities. Das (2002), for example, shows that jump processes capture empirical features of the data that would not be captured by Gaussian models. In an appealing development from an economic perspective, Das (2002) links surprise jumps in interest rates to information surprises and to Federal Reserve intervention effects in particular. Building on this intuition, Johannes (2004) finds evidence for the presence of jumps and extends the literature by investigating the statistical and economic role of jumps. Specifically, Johannes (2004) introduces a simple and flexible model of Treasury rates and develops a non-parametric technique for estimating the drift, diffusion, jump intensity and parameters of the jump distribution. The results obtained indicate that jumps play an important and dominant statistical role in interest rate dynamics with infrequent but large movements dominating the contribution to the total variance of interest rate changes. In pursuit of a more fundamental economic motivation for the cause of these jumps, jump times and sizes are reconciled with news arrivals. Extracting the specific sub-samples 1979-1982 and 1991-1993, each large interest rate move during these periods that are identified as jumps are found to coincide with macroeconomic news arrivals. For the sub-period 1991-1993, for example, Federal Reserve target rate changes, unemployment announcements, the Soviet coup, the outbreak of the Gulf War and the 1992 Bush-Clinton presidential debates are coincident with interest rate jumps, providing some initial evidence that information about the macroeconomy enters the term structure through these surprise jumps. Moreover, such jumps only occur in response to the unexpected components of these announcements.

4.2.2 Realised Volatility

To aid and add structure to this review, it is useful to introduce some notation.[2] Given the overwhelming evidence that jumps are an integral part of the (log) price process, the following equation defines the jump-diffusion model that forms the cornerstone of this and other recent work:

[2] A more robust treatment of the theoretical background to this work is provided in the following section.

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), \tag{4.1}$$

where $\mu(t)$ is a continuous and locally bounded variation process, $\sigma(t)$ is a strictly positive stochastic volatility process which allows for occasional jumps in volatility, $W(t)$ is a standard Brownian motion, and $q(t)$ is a counting process with possible time-varying intensity $\lambda(t)$. This implies that $P[dq(t)=1]=\lambda(t)dt$, and $\kappa(t)$ measures the size of the corresponding discrete jumps in the logarithmic price process.

Discretely sampled Δ-period high frequency returns are defined as $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$. In parallel with the advancement of parametric continuous-time models and methods, powerful non-parametric techniques have been developed to measure the (latent) volatility of asset returns, which rely on the information contained in high frequency data. Realised variation, calculated as the sum of Δ-period high frequency intraday squared returns,

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r_{t+j\cdot\Delta,\Delta}^{2}, \tag{4.2}$$

provides a model free, asymptotic (as the sampling frequency becomes finer), ex-post measure of the daily latent return variation.[3] Although much of the recent work on realised volatility stems from Andersen and Bollerslev (1998b), who argue that GARCH models provide good volatility forecasts when evaluated against the more accurate realised variance measure of volatility rather than the more noisy squared daily return measure, the use of historical high frequency returns data in computing ex-post lower frequency sample variances has a long precedent in the empirical finance literature. For example, Poterba and Summers (1986), French et al. (1987) and Schwert (1989) rely on monthly measures of variance calculated from daily returns, while Schwert (1990b), Hsieh (1991), Taylor and Xu (1997) and Andersen and Bollerslev (1998a) exploit intraday data to produce daily sample return variance and volatility measures.

The early literature on realised volatility investigated its distributional properties, focusing on the distributional properties of returns standardised by

[3] Realised volatility, which is more commonly referred to in the literature and in this chapter, is defined simply as the square root of this realised variation measure, however, it is common for both terms to be used interchangeably throughout the literature.

realised volatility in particular. For example, Andersen, Bollerslev, Diebold and Ebens (2001) find that the unconditional distributions of realised variances and covariances of five-minute returns for individual stocks on the Dow Jones Industrial Average are highly right skewed, while the realised logarithmic standard deviations and correlations are approximately Gaussian. Returns scaled by realised standard deviations are also found to be approximately Gaussian and the time series properties of realised volatilities and correlations show strong temporal dependence and are characterised by long memory processes. Similar results are documented by Andersen, Bollerslev, Diebold and Labys (2001) for a decade of five-minute Deutsche Mark-US Dollar and Yen-US Dollar exchange rate returns. In particular, realised variances, standard deviations and covariances show right skewed and leptokurtic distributions, whereas the distributions of logarithmic standard deviations and correlations are approximately Gaussian. In addition, Andersen, Bollerslev, Diebold and Labys (2001) find that volatility movements are highly correlated across the two exchange rates, that this correlation between the exchange rates increases with volatility, that there is strong evidence of volatility clustering, and volatility persistence remains high even at lower frequencies in accordance with slowly mean reverting or fractionally integrated series. Extending this work, Andersen, Bollerslev, Diebold and Labys (2000a) report that exchange rate returns standardised by realised volatility are approximately Gaussian, which the authors interpret as support for a jumpless diffusion process for asset prices, since the presence of jumps are likely to violate the normality of the standardised returns. The important contribution of these studies is the recognition and treatment of realised volatility as the object of intrinsic interest, rather than merely as an ex-post criterion for evaluating the performance of parametric conditional volatility models.

In related work in different market settings, Areal and Taylor (2002) document that neither the distribution of the logarithm of volatility nor that of returns standardised by realised volatility is exactly normal for five-minute FTSE 100 futures returns; however, in support of previous findings, the distribution is nearly lognormal, with the main empirical discrepancy away from log normality being an excess probability of extremely high levels of volatility. This discrepancy may be due to the presence of extreme jumps caused by macroeconomic news releases, events that Areal and Taylor (2002) recognise when investigating the intraday pattern of high frequency FTSE 100 index futures volatility. Concerning the time series properties, FTSE 100 index futures realised volatility is found to be best described by a long memory process. In further investigation of futures markets, Thomakos and Wang (2003) consider five-minute returns on the T-Bond, S&P 500, Eurodollar and Deutsche Mark futures contracts over a five year period. Logarithmic realised standard deviations are found to exhibit long memory and approximate Gaussianity, while standardised returns also exhibit approximate Gaussianity, but are serially uncorrelated. Rather than relying on descriptive statistics and graphs to determine distributional properties, as much of the previous literature had done, Thomakos and Wang (2003) present these results by performing a variety of formal statistical tests and conducting a simulation study to examine the properties of these tests in the presence of long memory.

4.2.3 Quadratic Variation and Realised Power Variation

Beyond the early empirical treatment described above, the theory of realised variation has been addressed more formally in the pioneering work of Andersen, Bollerslev and Diebold (2007a), Andersen, Bollerslev, Diebold and Labys (2003), Barndorff-Nielsen and Shephard (2001, 2002a, 2002b, 2004a) and Comte and Renault (1998). Building on the foundation of a continuous-time arbitrage-free process, Andersen, Bollerslev, Diebold and Labys (2003) extend the literature to describe a rigorous multivariate theoretical framework for the use of realised variation and covariation. Crucial to this framework is the general representation of the instantaneous return to any arbitrage-free logarithmic price process as the sum of a predictable finite variation mean component and a local martingale,

$$r(t) = \mu(t) + M(t) = \mu(t) + M^{c}(t) + M^{J}(t)\,. \tag{4.3}$$

This provides a unique, canonical decomposition of the instantaneous return, $r(t)$, into an expected return component, $\mu(t)$, and a (martingale) innovation, $M(t)$. The local martingale may be further decomposed into a continuous sample path, infinite variation local martingale component, $M^c(t)$, and a compensated jump martingale, $M^J(t)$, if the possibility of jumps is assumed to exist. As documented by Andersen, Bollerslev and Diedold (2007a), a first step in the study of return variance concentrates on the martingale component of the return decomposition of equation

(4.3), measuring the strength of the unexpected return variation over a period of time. However, since continuous records of price data are not available and are unlikely to be available because of market microstructure effects, the integrated (or latent) volatility of asset returns is unobservable in practice, and therefore research on volatility measures is focussed on the average realised volatility over a discrete time interval.[4] Despite this drawback, the unique semi-martingale return decomposition implies that the martingale innovation component has a quadratic variation process, and this forms the foundation for the general notion of volatility.

The theory of quadratic variation, as noted in Andersen, Bollerslev and Diebold (2007a), Andersen, Bollerslev, Diebold and Labys (2003) and Barndorff-Nielsen and Shephard (2002a, 2002b, 2004), plays a crucial role in the theoretical development of realised volatility in a number of ways. First, under suitable conditions, realised variation is an unbiased and consistent measure of return variation and, specifically, in the limit as the sampling frequency approaches infinity, the sum of intraday squared returns converges uniformly in probability to the quadratic variation process of the return process. Defining the quadratic variation process of equation (4.1) as

$$[r,r]_t = \int_0^t \sigma^2(s)ds + \sum_{0<s\leq t} \kappa^2(s), \tag{4.4}$$

where $\int_0^t \sigma^2(s)ds$ is the integrated volatility of the continuous sample path and $\sum_{0<s\leq t} \kappa^2(s)$ is the sum of squared jumps between times 0 and t, these two components measuring the respective contributions of the continuous sample path and jumps to total return variation. The asymptotic probability limit is then expressed as

$$RV_{t+1}(\Delta) \rightarrow \int_t^{t+1} \sigma^2(s)ds + \sum_{t<s\leq t+1} \kappa^2(s). \tag{4.5}$$

[4] See section 4.2.5 for discussion of market microstructure frictions.

This implies that the realised variation measure calculated from high frequency returns offers a consistent estimator of the quadratic variation process and, intuitively, suggests that the quadratic variation process represents the cumulative realised sample path variability of returns over a particular (small) interval. This consistency result has been investigated in the influential work of Barndorff-Nielsen and Shephard (2001, 2002a, 2002b, 2004a). In particular, Barndorff-Nielsen and Shephard (2002a) derive a mixed normal asymptotic distribution of the difference between realised volatility and actual volatility in the context of general stochastic volatility models in the absence of jumps, enabling the evaluation of the precision of realised volatility as an estimator of quadratic variation to be evaluated. In establishing the second order properties of actual variation and the realised variation error, Barndorff-Nielsen and Shephard (2002a) extend analysis beyond the familiar consistency result to derive a more refined measure of the uncertainty of the realised volatility error term. The limit theorem does not depend on the specification of the drift or risk premium parameters in the stochastic volatility model, and permits the volatility process to be non-stationary whilst simultaneously exhibit long memory, include deterministic intraday patterns and leverage effects, and also allows for the empirical regularity that the variance of the realised volatility error increases with volatility. Another important development of that study, which forms an important element of this chapter, is the introduction and definition of realised quarticity, the second order moment of realised variation. Defined as the scaled sum of the fourth powers of intraday returns, realised quarticity provides a consistent estimator of the unobservable spot quarticity, again providing a model free metric calculated from high frequency returns, and represents a special case of the more general power variation measures that are formalised in subsequent studies. The finite sample performance of realised volatility and its asymptotic properties are analysed by Barndorff-Nielsen and Shephard (2002b, 2004), and extended to a more general stochastic volatility model and under alternative transforms, finite sample corrections and alternative estimates of quarticity.

The second important feature of the theory of quadratic variation is that under the arbitrage-free assumption that there are no predictable jumps in the return process and, noting that the quadratic variation of finite variation continuous processes is zero, the continuous finite variation component in the canonical return decomposition of equation (4.3), $\mu(t)$, becomes irrelevant for the quadratic variation.

This implies that the quadratic variation of the return process is determined exclusively by the quadratic variation of the martingale innovation. This variation measure, therefore, is induced only by the innovations to the return process and, as such, the quadratic variation constitutes a unique and invariant ex-post realised volatility measure that is essentially model-free. Moreover, as described above, it is possible to approximate this quadratic variation process arbitrarily well through the use of ever finely sampled high frequency squared returns, an approach that remains consistent independent of the expected return process.

Third, Andersen, Bollerslev and Diebold (2007a) and Andersen, Bollerslev, Diebold and Labys (2003) show that the quadratic variation process is the most important factor for return volatility measurement and forecasting. In addition, as shown in equation (4.3), the quadratic variation process can be decomposed to the sum of two factors, the quadratic variation of the continuous infinite-variance local martingale, and the contribution from jumps as measured by the squared jump size. Realised volatility, which serves as an unbiased and consistent non-parametric estimator of the quadratic variation process, incorporates the effect of realised jumps in the price process. Jumps, therefore, contribute to the realised return variability and forecasts of volatility must account for the potential occurrence of such jumps. Jumps are the subject of intrinsic interest in this chapter and the remaining review here details the development of the realised volatility literature that has prompted the introduction of new non-parametric techniques allowing the contribution of the jump component to quadratic variation to be separated from the continuous infinite variance local martingale component.

In extension to the theory of quadratic variation, Barndorff-Nielsen and Shephard (2003, 2004b, 2004c) have generalised the theory of realised variation to 'realised power variation'. Barndorff-Nielsen and Shephard (2003) introduce the idea of realised power variation, defined as the sum of absolute powers of increments (returns) of a process,

$$RPV_{t+1}(\Delta, p) \equiv \Delta^{1-p/2} \mu_p^{-1} \sum_{j=1}^{1/\Delta} \left| r_{t+j \cdot \Delta, \Delta} \right|^p . \tag{4.6}$$

The empirical properties of the sum of intraday absolute returns have been studied previously by Andersen and Bollerslev (1997, 1998a), but, although the use of intraday absolute returns has been attractive to researchers, because they are less sensitive than squared returns to possible large movements in high frequency data, subsequent work has abandoned their use due to the lack of appropriate asymptotic theory for their sums. Barndorff-Nielsen and Shephard (2003) fill this void by deriving this theory for certain types of semi-martingales. Specifically, as the number of high frequency returns approaches infinity, scaled realised power variation converges in probability to integrated power volatility and follows, asymptotically, a normal variance mixture distribution. This asymptotic analysis represents a significant extension of the usual quadratic variation result, and the limiting distribution theory considerably strengthens the consistency result. The theory of realised power variation applies to any positive order, but two special cases identified are realised volatility (the sum of squared absolute returns), which implies an order of two and is identical to the sum of squared returns, and realised absolute variation (the sum of absolute returns) implying an order of one.

In another significant contribution to the realised volatility literature, Barndorff- Nielsen and Shephard (2004b) introduce a generalisation of the concepts of realised variation and realised power variation, called 'realised bipower variation', and show that this and realised power variation measures are robust to rare jumps. Defined as the normalised sum of products of adjacent high frequency absolute returns raised to particular positive powers, realised bipower variation is shown to provide a consistent estimator of integrated power volatility, and with integrated variance as a special case. The latter is a simple version of this measure where the respective powers are both equal to one and is represented by:[5]

$$BV_{t+1}(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} \left| r_{t+j\cdot\Delta,\Delta} \right| \left| r_{t+(j-1)\cdot\Delta,\Delta} \right|. \tag{4.7}$$

The influential contribution of this and more general results is that this measure offers a new way of making inferences and predicting integrated variance in stochastic volatility models, which Barndorff-Nielsen and Shephard (2004b) describe as 'perhaps the single most important term in the econometrics of volatility'.

[5] For a discussion of the more general cases and derivation of the special cases, see Barndorff-Nielsen and Shephard (2004b).

Furthermore, these results are robust to the inclusion of a compound Poisson process in the price process, thereby allowing for rare jumps.

In addition to the introduction and analysis of realised bipower variation as their main contribution to the literature, the special case identified by Barndorff-Nielsen and Shephard (2004b) represented in equation (4.7) above has a great deal of applied interest and provides the cornerstone of this chapter. Under the condition that adjacent absolute high frequency returns are raised to the power unity, realised bipower variation is a consistent estimator of integrated variance, the continuous component of quadratic variation. The difference between the quadratic variation, which includes both continuous and jump contributions, and this special case of bipower variation, therefore isolates the contribution to quadratic variation of the jump component alone:

$$RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \rightarrow \sum_{t<s\leq t+1} \kappa^2(s). \tag{4.8}$$

Furthermore, the probability limit of this difference is shown to be finite and positive and measures the quadratic variation of the jump process. In a simulation exercise, Barndorff-Nielsen and Shephard (2004b) show that in finite samples, the realised bipower variation estimator performs well and is improved upon further by invoking a non-negativity condition on the jump contribution. In empirical work using five-minute US Dollar/DM data from 1st December 1986 to 30th November 1996, Barndorff-Nielsen and Shephard (2004b) consider two periods of high realised variance, the first identifies a large jump contribution in response to unanticipated US trade deficit news, whereas the second does not identify any jumps, with high volatility being caused by high estimated integrated variance. Barndorff-Nielsen and Shephard (2004b) is the first study to decompose the quadratic variation into contributions from the continuous and jump components of the logarithmic price and has motivated recent interest in the identification and measurement of jumps. It is also the first study to propose a possible link between jumps and macroeconomic news announcements, which provides the motivation for this chapter.

4.2.4 Non-Parametric Jump Detection

The econometrics of testing for jumps has been formalised by Barndorff-Nielsen and Shephard (2006). Advancing their previous theoretical work on bipower variation, Barndorff-Nielsen and Shephard (2006) provide an asymptotic distribution theory for some non-parametric tests of the hypothesis that asset prices have continuous sample paths.[6] In constructing the linear test, the difference between realised variation and realised bipower variation provides a measure of the quadratic variation of the jump component, which is standardised by the square root of the integrated quarticity. Since integrated quarticity is latent, feasible tests rely on estimating integrated quarticity using realised quadpower variation, which is a consistent estimator under both the null hypothesis that there are no jumps in the log-price process and the alternative hypothesis that jumps exist, thus ensuring that the test has power under the alternative hypothesis. To assess the proportional contribution of jumps to quadratic variation, a ratio jump test is also presented. The jump contribution is divided by the realised variation to form the ratio, which is then standardised appropriately by its second moment. Further, to maintain sensible estimated values for this appropriate denominator, as dictated by the asymptotic theory, Barndorff-Nielsen and Shephard (2006) also present an adjusted ratio jump test. The linear, ratio and adjusted ratio versions of these jump tests are illustrated using simulations, with the adjusted ratio jump test performing well in small samples. When applied to the sample of five-minute US Dollar/DM exchange rate data mentioned above, there is strong empirical evidence for the presence of specific jumps, with particularly large jumps coinciding with US macroeconomic news announcements.[7]

Whilst Barndorff-Nielsen and Shephard (2006) focus their research on providing the asymptotic theory to enable testing for jumps, there have been other recent studies extending this area. In the first of these, Huang and Tauchen (2005) undertake extensive simulation exercises to assess the finite sample performance of various jump test statistics and reinforce these findings empirically. The framework

[6] See also Bandi and Nguyen (2003) and Johannes (2004) for alternative non-parametric jump detection techniques and Aït-Sahalia (2004) for a likelihood based statistical method to distinguish volatility from jumps.

[7] In a further advance in this theory and as a by product of their research on the econometrics of testing for jumps, Barndorff-Nielsen and Shephard (2006) derive the consistency result of realised bipower variation under much weaker conditions than previously demonstrated (Barndorff-Nielsen and Shephard, 2004b).

for this work is the measurement of the jump contribution to quadratic variation as the difference between realised variation and realised bipower variation, which follows directly from Barndorff-Nielsen and Shephard (2006). Scaling this quantity by realised variation enables calculation of the relative contribution of jumps in the spirit of the ratio jump test of Barndorff-Nielsen and Shephard (2006) mentioned above. Huang and Tauchen (2005) offer numerous alternative test statistics based on these linear and ratio measures, using realised quadpower quarticity and realised tripower quarticity (an extension to the theory of bipower variation) as alternative estimates of integrated quarticity and using logarithmic and maximum value adjustments to improve the finite sample performance of the tests. They document numerous findings as follows.

First, the choice between realised quadpower quarticity and realised tripower quarticity does not matter in any material way for the estimation of integrated quarticity. Second, the linear jump test exhibits a size distortion towards over-rejecting in the right hand tail at significance levels conventional for this type of test. Log-transformations and ratio jumps statistics appear to correct any size distortions except in the extreme right hand tail. Sampling frequency also has a significant impact on size, supporting the consistency result that as the sampling frequency decreases then asymptotic normality becomes a poorer approximation to the finite sample distribution of the test statistic. Under the null hypothesis that there are no jumps in the data generating process, and using critical values from the normal distribution, the test statistics signal more false jumps using lower frequency returns. Third, Huang and Tauchen (2005) show that the statistics successfully detect jumps, although as the sampling frequency decreases, the test statistics signal fewer instances of jumps than actually occur. Fourth, jump intensity and jump size have positive effects on the power of the tests, whilst sampling frequency has a negative effect on power. Huang and Tauchen (2005) suggest, therefore, that for lower sampling frequencies, the statistics neglect true jumps when jumps exist and also signal more false jumps when there are no jumps, thus making a very strong case for the need to use high frequency data for jump detection using these types of statistics. In an empirical application, Huang and Tauchen (2005) use five-minute observations of the S&P 500 Index cash and futures markets. Their work shows that the statistics indicate far more jumps than would be expected under a purely diffusive model, confirming the strong evidence for the existence of jumps. Jumps contribute between

4.4 and 7.3% of the total realised variation of daily stock price movements, indicating that jumps are a statistically important component of aggregate stock price movements.

In related work, Tauchen and Zhou (2005) identify realized jumps in financial markets, estimate parametrically the jump intensity, jump mean and jump variance, and examine the behaviour of these measures over time. The finite sample results of simulation exercises show that the jump parameters are consistently estimated as the sample size increases, however, the estimation accuracy does not change as the data frequency increases from five to one-minute. Unlike the parameter estimation results, the Wald test statistics performed on these parameters, based on asymptotic standard errors, converges to its asymptotic level as the data frequency increases rather than as the sample size increases. Applying these findings to five-minute S&P 500 Index data, Tauchen and Zhou (2005) find that jumps contribute 5.86% of total price variation, similar to the 7.33% reported by Huang and Tauchen (2005). A jump rate of 10.16% measures the proportion of trading days containing jumps, which implies about 25 jumps per year. This large number of jumps per year, together with a positive mean value (1.51% annually) contradicts the presumptions and previous findings in the literature that jumps are rare and negatively skewed. This, Tauchen and Zhou (2005) suggest, may be reconciled with the notion that significant jumps in financial markets are related to the surprise responses to macroeconomic news announcements. Furthermore, the clustering and amplitude of jumps are found to change over time implying time dependent jump intensity and jump size distribution.

In extension of the econometrics of jump detection, Andersen, Bollerslev and Diebold (2007b) present a practical and robust framework for non-parametrically measuring the jump component in asset return volatility. Building on the recent theoretical developments of Barndorff-Nielsen and Shephard (2004b, 2006) and the extensive simulation exercises of Huang and Tauchen (2005), the emphasis of this work is firmly on the economic importance and relevance of the continuous and jump components of total return variation. More specifically, using more than a decade of five-minute returns covering foreign exchange (DM/$), equity futures (US S&P 500 Index) and interest rate futures (30 year US Treasury yield) markets, Andersen, Bollerslev and Diebold (2007b) take advantage of the isolation and measurement of the jump component of price variation to improve the forecasting of volatility. Confirming the previous evidence on the importance of jump contributions, the means of the jump series are found to contribute 7.2%, 14.4% and 12.6% to the mean realised variation for the DM/$, S&P500 and T-bond markets, respectively. The time series statistics show that, although the jump series display statistically significant serial correlation at conventional significance levels, the Ljung-Box test statistics are markedly lower for the jump series than the corresponding realised volatility series. This, Andersen, Bollerslev and Diebold (2007b) suggest, indicates less dynamic dependence in overall quadratic variation attributable to the jump component as compared to the continuous component.

Motivated by these results, Andersen, Bollerslev and Diebold (2007b) build on the asymptotic theory of Barndorff-Nielsen and Shephard (2006) and refine the existing non-parametric techniques to identify statistically significant jumps that are free from measurement error and adjusted for the effects of market microstructure noise. A further contribution of this work considers days in the sample that exhibit particularly large, significant jumps, which, in support of the assertions of Barndorff-Nielsen and Shephard (2006), are reconciled with specific scheduled macroeconomic news announcements. These days are contrasted with those of extremely high daily realised volatility caused by smooth intraday price moves, highlighting the different behaviour that high frequency prices may exhibit and the different contributions of the two components to quadratic variation. The remaining contribution of Andersen, Bollerslev and Diebold (2007b) presents summary and time series statistics for statistically significant jumps and makes use of this latter series in volatility forecasting models. Specifically, the proportion of days containing significant jumps is far greater than the expected proportion under the null hypothesis of a purely continuous price process and also far greater than the jump intensities estimated by specific parametric jump-diffusion models applied to daily and lower frequency returns, which typically suggest only a few jumps per year.[8] There is evidence of serial dependence in the significant jump series, although test statistics are much lower than those for the realised variation series. Furthermore, by investigating the durations between jumps and the sizes of the corresponding jumps, there is strong evidence for clustering in the occurrences of significant jumps and in the durations between them. Andersen, Bollerslev and Diebold (2007b) also examine jump

[8] See the evidence presented in the references discussed in section 4.2.1.

intensity and jump size over time and present evidence of temporal dependence in the jump arrival processes and jump sizes, revealing a more complex dynamic dependence in the significant jump time series.

Finally, in a most innovative contribution, Andersen, Bollerslev and Diebold (2007b) apply the continuous and jump components of price variation to a heterogeneous autoregressive realised volatility model (HAR-RV) for forecasting realised volatility, which includes lagged values of realised volatility measured at different and lower frequencies than the daily level of the dependent variable. By explicitly decomposing the realised volatilities that appear as explanatory variables into the continuous sample path variability and jump variation, Andersen, Bollerslev and Diebold (2007b) show that most of the jump coefficients, for most markets and forecast horizons, are insignificant, meaning that the predictability in the HAR-RV regression is almost exclusively due to the continuous sample path components. The use of realised volatilities as explanatory variables rather than coarser squared returns measured at lower frequency provides substantial gains in forecasting accuracy, with additional gains achieved when decomposing realised volatility into its constituent components.[9]

Whilst the contributions of Barndorff-Nielsen and Shephard (2006), Huang and Tauchen (2005), Tauchen and Zhou (2005) and Andersen, Bollerslev and Diebold (2007b) rely on high frequency data to allow the identification of significant jump contributions to total asset return variation, the techniques presented are limited to isolating days during which jumps occur. The methods, therefore, preclude the measurement of separate contributions from numerous jumps on particular days and prevent the exact timing of jumps. Both of these issues are addressed by the very recent work of Andersen, Bollerslev and Dobrev (2007) and Andersen, Bollerslev, Frederiksen and Nielsen (2006). The focus of the study by Andersen, Bollerslev and Dobrev (2007) is the adequacy of continuous-time jump-diffusion models for describing the characteristics of observed high frequency asset return distributions. Recognising the widely documented finding that the conditional distributions of asset returns typically show fat tails and extreme outliers and citing the recent empirical

[9] An improvement in forecasting performance when using realised volatilities calculated from high frequency returns confirms earlier empirical evidence (Andersen, Bollerslev, Diebold and Labys (2003), Andersen, Bollerslev and Meddahi (2005) Bollerslev and Wright (2001), Hansen and Lunde (2006a), and Martens (2002), for example) and supports the analytical results of Andersen, Bollerslev and Meddahi (2004).

work showing the importance of incorporating jumps in continuous-time models to provide a satisfactory characterisation of the daily return process, Andersen, Bollerslev and Dobrev (2007) present a jump detection and extraction procedure in order to allow the distributional characteristics of jump adjusted returns to be investigated.[10] The construction of a jump adjusted series of intraday returns requires specific knowledge about the number of jumps occurring during a particular day and the particular intervals in which they occur. This new jump detection technique considers whether a randomly selected intraday return, given an appropriately scaled realisation of bipower variation (which is robust to jumps) is subject to a jump. The procedure relies on the assumption that volatility is constant over the course of a trading day in order to develop a feasible approach for the identification of exact jump timing, and its practical performance is analysed using simulation evidence. The results reveal that the test performs well for a variety of relevant models and even tends to outperform the existing procedure inspired by Barndorff-Nielsen and Shephard (2006) in identifying days with jumps.

As alternative approaches to the exact timing of jumps, Andersen, Bollerslev, Frederiksen and Nielsen (2006) propose two non-parametric procedures for detecting and estimating jumps, which, in accordance with Andersen, Bollerslev and Dobrev (2007), are used to transform intraday returns in order to analyse the impact and distributional implications of jumps for stock returns. This simple detection method follows the earlier techniques of Barndorff-Nielsen and Shephard (2006), Huang and Tauchen (2005) and Andersen, Bollerslev and Diebold (2007b) in that it is based on the premise that jumps are rare events and, more specifically, that there is at most only one jump during a particular day. Squared jumps are then estimated as the difference between realised variation and realised bipower variation, with sufficiently large values relative to the standard normal distribution for a given critical value indicating the presence of a jump during that particular day. The square root of this measure estimates the jump, which is then assigned the same sign as the return causing the largest absolute return on that day. However, this simple method is

[10] Further adjustments to intraday returns transform jump-adjusted returns into 'event' or 'financial' time rather than calendar time to account for leverage or volatility feedback effects. However, since the primary interest of this study is the jumps, a comprehensive coverage of these effects is left for future work. Although it may be possible that a leverage or volatility feedback effect could work through the jump component, the empirical evidence of Bollerslev, Kretschmer, Pigorsch and Tauchen (2005) suggests that the asymmetry works primarily through the continuous component. See also the recent work of Bollerslev, Litvinova and Tauchen (2006) for a treatment of these issues.

limited to showing whether the difference between the realised variation and bipower variation is large enough to indicate the presence of one or more jumps during the day.

The sequential jump detection method extends this approach by sequentially identifying the significant jumps through the differences between the largest squared intraday returns and the average of the remaining squared returns. Specifically, in the first iteration of the test, a jump is identified during a particular day if the difference between realised variation and bipower variation is sufficiently large, where realised variation is based on the sum of all squared intraday returns. The contribution of the jump to the total daily variation is identified as the difference between the largest squared return and the average of the other remaining squared returns. The interval containing the jump is readily detected as the interval containing this maximum squared return, with the jump estimated by the return during that interval. To allow for more than one jump during a particular day, the procedure is repeated for a second iteration for the same trading day. The sequential step of the procedure replaces the largest squared return (containing the jump) identified in the first iteration with the average of the remaining squared returns. The summation of these squared returns then represents the realised variation corrected for one jump, which is then compared to realised bipower variation to detect any further possible jump. If the new test statistic which uses the jump-corrected realised variation detects another jump, then there are at least two jumps on this particular trading day. The contribution to total price variation is therefore the second largest squared return less the average of the remaining squared returns, and the interval containing the second jump can be identified easily, with the second jump estimated as the return occurring during this interval. The procedure is continued until the difference between the jump adjusted realised variation and realised bipower variation is not sufficiently large. On comparing the simple and sequential jump detection techniques, Andersen, Bollerslev, Frederiksen and Nielsen (2006) report that the less informative simple method captures the same overall features as the more elaborate sequential procedure, but, importantly, the sequential procedure identifies directly the exact intraday times of all jumps.

The ability of the technique proposed in Andersen, Bollerslev and Dobrev (2007), and the sequential procedure of Andersen, Bollerslev, Frederiksen and Nielsen (2006), to identify multiple jumps within a single day, along with the precise times of those jumps, provides superior information to earlier tests. Indeed, the accurate detection of intraday jumps underpins the empirical work of this chapter, which will focus on the economic determinants of these jumps.

4.2.5 Market Microstructure Noise

Before concluding this review, there is one final issue that has received increasing attention in the recent literature and therefore warrants some brief discussion. The advances made recently in the development of continuous-time semi-martingale jump-diffusion models describing the asset price process and the construction of non-parametric techniques for the measurement of volatility and its separate continuous and jump components rely crucially on the availability of high frequency data. The consistency arguments for realised volatility and realised bipower variation presented throughout the literature are based on the assumption that the sampling frequency becomes ever finer. However, the assumption that prices follow a semi-martingale is violated as the sampling frequency becomes higher due to market microstructure frictions, such as discrete price grids, non-synchronous trading and bid-ask bounce, which imply that returns are either zero or larger than would be expected over such a small time interval.[11] Typically, the true return variation over such short intervals is lower than the lowest permitted by the price grid, so the observed price process is contaminated by a market microstructure noise component. The issue of market microstructure noise has received considerable attention in recent works, which have been devoted to both determining the best ways to account for these market microstructure frictions and also to the more practical choice of optimal sampling frequency in the calculation of realised volatility.[12] Although some recent studies impose more complex structures for the microstructure noise (Bandi and Russell, 2005; Hansen and Lunde, 2006b), the theoretical and empirical development of the analysis and implications of microstructure noise have been founded on the very descriptive case that the noise follows an independently and identically distributed Gaussian distribution.

[11] See also Neftci (2007) for further arguments concerned with 'barrier', 'stop-loss' and 'spread' trading.

[12] See, for example, Aït-Sahalia et al. (2005), Andersen, Bollerslev, Diebold and Labys (2003), Bandi and Russell (2005, 2006), Bollen and Inder (2002), Corsi et al. (2001), Hansen and Lunde (2006b), Oomen (2005), and Zhang et al. (2005).

In the specific context of jump detection, market microstructure noise plays a crucial role since it is important to distinguish between true jumps and spurious jumps caused by the market microstructure noise. Assuming i.i.d Gaussian noise contaminates the latent semi-martingale logarithmic price process, Huang and Tauchen (2006), Andersen, Bollerslev and Diebold (2007b), and Andersen, Bollerslev and Dobrev (2007) all show that discretely sampled observed returns consist of the true return plus a first order moving average process. This random price error induces both excess variation into the realised volatility measure, which cumulates proportionally with the sampling frequency, and spurious negative serial correlation between adjacent returns. The consequence of these symptoms is that, in the presence of noise, realised volatility becomes an upward biased and inconsistent estimator of the true quadratic variation. The realised bipower variation estimator of integrated variation is also upward biased in the presence of noise, but since this relies on adjacent returns the spurious serial correlation generated by the noise presents an additional source of bias as compared to the realised variation measure. Similar arguments apply to the realised tripower quarticity estimator of integrated quarticity. Furthermore, Huang and Tauchen (2006) show that in the presence of noise, the jump test statistic is biased downwards and therefore in favour of finding fewer jumps. This is because the numerator, as the difference between realised variation and realised bipower variation, is negatively biased, whilst the noise also inflates the estimate of integrated quarticity used to form the scale in the denominator of the jump test statistic. Together, the two effects bias the statistic against rejection.

The impact of market microstructure noise on realised variation is most easily controlled through the choice of sampling frequency. Optimal sampling frequency can be determined by the use of volatility signature plots, and the empirical evidence suggests that the bias in realised volatility generally disappears at the five-minute frequency. To counter the additional bias affecting power variation measures, resulting from the spurious serial correlation between adjacent returns, Andersen, Bollerslev and Diebold (2007b) suggest calculating these measures using staggered returns rather than adjacent ones. The staggering of returns breaks the serial correlation caused by the market microstructure noise, and, importantly, Barndorff-Nielsen and Shephard (2005) have shown that in the absence of the noise component the staggered versions of the realised power variation measures remain consistent for the corresponding integrated variation measures. As such, by replacing the standard one-lag realised bipower variation and tri-power quarticity measures with their staggered counterparts, the jump test statistic will be asymptotically standard normally distributed and, by alleviating the influences of market microstructure noise, should result in more accurate finite sample approximations. The simulation results of Huang and Tauchen (2005) show that the jump ratio statistic calculated with staggered power variation measures performs admirably for a wide range of market microstructure contaminants. Staggering by a longer lag length can also break higher order serial correlation that may arise from noise structures that extend beyond the i.i.d Gaussian assumption considered so far in the literature.[13]

4.2.6 Jumps and News

Along with the strong evidence for the need to allow for jumps in continuous-time stochastic volatility asset pricing models, as shown by the parametric estimation methods detailed in section 4.2.1, empirical studies incorporating high frequency data also reveal abrupt price jumps. Encouragingly, from market efficiency and economic perspectives, the largest returns coincide with the release of macroeconomic news, with unanticipated announcements generating the most extreme movements.[14] The relationships between macroeconomic fundamentals and financial markets have been analysed for many years, and have already been reviewed in earlier chapters, but there has been a surge in this literature with the recent availability of high frequency intraday data. The pioneering work of Andersen and Bollerslev (1998a), for example, evaluates (parametrically) the impact of macroeconomic announcement indicators on five-minute Deutsche Mark-Dollar volatility and finds that the Employment Report, GDP, trade balance and durable goods orders are the most significant US announcement, whilst the important German announcements are Bundesbank meetings and M3 supply figures. In support of these findings, Bollerslev et al. (2000) investigate five-minute returns from the US Treasury bond market and show even more volatile reactions to news, with the

[13] Andersen, Bollerslev and Dodrev (2006) present an alternative adjustment to account for market microstructure noise, which involves the estimation of the noise variance. Since jumps are not considered in the existing theoretical work dealing with market microstructure noise, and the presence of jumps may complicate the estimation of the noise process, this type of adjustment represents an intriguing embryonic approach to the problem.

[14] Earnings announcement effects on stock markets have also received considerable attention and Maheu and McCurdy (2004) offer a pertinent recent investigation.

Humphrey-Hawkins testimony, the Employment Report, PPI, employment cost, retail sales and the NAPM survey having the largest impact.

Examination of the short run reaction of asset returns to macroeconomic announcements has been enhanced in the recent work of Andersen, Bollerslev, Diebold and Vega (2003, 2007), who move the focus of this area towards quantifying the surprise component of news and using it in explaining conditional returns. Investigating five-minute returns on five exchange rates, Andersen, Bollerslev, Diebold and Vega (2003) show that conditional mean adjustments of exchange rates to news occur quickly, are characterised by jumps, that an announcement's impact depends on its timing relative to other related announcements and whether the announcement time is known in advance, and that adjustment response patterns are characterised by a sign effect with bad news exhibiting a greater impact than good news. Confirming previous findings, the important US announcements, across all currencies, are the Employment Report, durable goods orders, trade balance, initial unemployment claims, NAPM index, retail sales, consumer confidence, and advance GDP. Extending this work across markets and countries, Andersen, Bollerslev, Diebold and Vega (2007) confirm the dramatic and short lived response of conditional asset returns to surprises in the announcement of US macroeconomic data, but also reveal that equity markets react differently to the same news dependent on the state of the economy, with negative responses to good news in expansions and positive responses to good news in recessions.

In brief summary, therefore, the results of empirical studies estimating parametric continuous-time stochastic volatility models demonstrate, overwhelmingly, the importance of including a jump component for replicating the distributional properties of asset returns more accurately. The availability of informative high frequency data has also shown convincing evidence for the presence of jumps in the sample paths of asset prices. Moreover, high frequency data has also prompted the development of non-parametric techniques for separating such jump components from the continuous sample path and there is considerable evidence for the existence of jumps, with jumps occurring far more frequently than parametric estimation techniques suggest. In a related literature, the use of high frequency data has also reconciled extreme price movements with the announcement of macroeconomic news surprises, showing that asset prices react vigorously to the arrival of unanticipated information, so offering an economic explanation as to the cause of violent price movements. This chapter builds on these recent findings by focusing on the non-parametric procedures for identifying significant jumps. Whilst there have been some illustrative examples linking jumps to news announcements, as documented in Barndorff-Nielsen and Shephard (2006), Andersen, Bollerslev and Diebold (2007b), and Johannes (2004) for example, such descriptive case studies have been largely confined to reinforcing the evidence for the presence of jumps and demonstrating the relative success of alternative techniques in order to identify genuine and significant jumps. By combining this latest continuous-time asset pricing literature with the high frequency time series analysis of macroeconomic announcement effects, as in Andersen, Bollerslev, Diebold and Vega (2003, 2007), this chapter presents a more detailed econometric treatment of the macroeconomic determinants of jumps, providing an innovative investigation of the systematic relationships between asset price jumps and the arrival of information relating to economic fundamentals.

4.3 ECONOMETRIC METHODOLOGY

This section provides a more rigorous explanation of the statistical and econometric techniques described in the literature review above, beginning with the decomposition of semi-martingales, quadratic variation and realised volatility and culminating in the non-parametric identification of jumps and intraday jumps. Although many of the studies reviewed earlier employ differing styles of notation, the descriptions of Andersen, Bollerslev and Diebold (2007a, 2007b), Andersen, Bollerslev and Dobrev (2007) and Huang and Tauchen (2005) are particularly strong influences on this section because of their elegance, simplicity and relatively more economic interpretation, which is more readily applied to the motivation of this study. It is important to note, however, that the development of jump detection techniques is largely attributable to the asymptotic theory provided by Barndorff-Nielsen and Shephard (2004b, 2006).

4.3.1 Theoretical Background

Beginning with first principles, $p(t)$ defines the univariate, risky logarithmic price process, which evolves in continuous-time over the interval $[0,T]$ where T is a finite integer. The continuously compounded return over the time interval $[t-h,\ t]$ is then calculated as

$$r(t,h) = p(t) - p(t-h), \qquad 0 \le h \le t \le T, \qquad (4.9)$$

with the cumulative return up to time *t* defined as

$$r(t) \equiv r(t,t) = p(t) - p(0), \qquad 0 \le t \le T, \qquad (4.10)$$

such that the period-by-period return is simply

$$r(t,h) = r(t) - r(t-h), \qquad 0 \le h \le t \le T. \qquad (4.11)$$

As documented by Andersen, Bollerslev and Diebold (2007a), a maintained assumption throughout is that, almost surely, the asset price process *(P)* remains strictly positive and finite, so that *p(t)* and *r(t)* are well defined over *[0,T]*. Andersen, Bollerslev and Diebold (2007a) assume, without loss of generality, the right-continuous left-limit (càdlàg) version of the process defined as $r(t) = r(t+)$ where $r(t+) \equiv \lim_{\tau \to t, \tau > t} r(\tau)$. The jumps in the cumulative price and return process are then

$$\Delta r(t) \equiv r(t) - r(t-), \qquad 0 \le t \le T, \qquad (4.12)$$

where $r(t-) \equiv \lim_{\tau \to t, \tau < t} r(\tau)$ defines the left-continuous right-limit (càglàd) version of the return process and continuity points for *r(t)* imply $\Delta r(t) = 0$. Invoking the standard assumptions of no arbitrage opportunities and a finite expected return, the log-price process constitutes a semi-martingale, which affords the following unique canonical return decomposition noted earlier in section 4.2.3:

$$r(t) = \mu(t) + M(t) = \mu(t) + M^c(t) + M^J(t), \qquad (4.3)$$

where $\mu(t)$ is a predictable and finite variation process, *M(t)* is a local martingale which may be decomposed further into $M^c(t)$, a continuous sample path, infinite variation local martingale, and $M^J(t)$, a compensated jump martingale. This decomposition expresses the instantaneous return as an expected return component and a martingale innovation. As noted in the literature review, the analysis of volatility is focused on the behaviour of this martingale innovation by investigating the quadratic variation of the semi-martingale return process.

To focus this discussion on a particular log-price model, the continuous-time jump-diffusion process, expressed in stochastic differential equation form, as traditionally used in asset pricing and forming the theoretical framework for a number of recent studies, is:[15]

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), \qquad 0 \le t \le T. \tag{4.1}$$

where $\mu(t)$ is a continuous and locally bounded variation process, $\sigma(t)$ is a strictly positive stochastic volatility process with a sample path that is right continuous and has well defined left limits, which allows for occasional jumps in volatility, $W(t)$ is a standard Brownian motion, and $q(t)$ is a counting process with possible time-varying intensity $\lambda(t)$. This implies that $P[dq(t)=1]=\lambda(t)dt$, and $\kappa(t)$ measures the size of the corresponding discrete jumps in the logarithmic price process. The quadratic variation of the cumulative return process, $r(t)$, is then defined as

$$[r,r]_t = \int_0^t \sigma^2(s)ds + \sum_{0<s\le t} \kappa^2(s), \tag{4.4}$$

which comprises the sum of the integrated volatility of the continuous sample path and the squared jumps between times 0 and t, these two components measuring the respective contributions of the continuous sample path and jumps to total return variation. It is important to note that, as explained in the prior literature review, since $\mu(t)$ is a finite variation continuous process, its quadratic variation is zero and so this term does not appear in equation (4.4). Several recent studies that deal with the parametric estimation of continuous-time stochastic volatility models have shown the importance of explicitly incorporating jumps in the price process along the lines of equation (4.1).[16] Inspired by the complementary non-parametric approach of

---

[15] For recent studies using this process see Andersen, Bollerslev and Diebold (2007b), Andersen, Bollerslev and Dobrev (2007), Andersen, Bollerslev, Frederiksen and Nielsen (2006), Barndorff-Nielsen and Shephard (2006), Huang and Tauchen (2005) and Tauchen and Zhou (2005).

[16] See, for example, Andersen, Benzoni and Lund (2002), Eraker et al. (2003), Eraker (2004) and Johannes (2004).

Andersen, Bollerslev and Diebold (2007b), Barndorff-Nielsen and Shephard (2006) and Huang and Tauchen (2005) to the identification and isolation of significant jumps, this chapter relies on high frequency data and recent, powerful asymptotic theory.

4.3.2 High frequency Data, Realised Volatility and Jump Identification

A continuous sample path for asset prices cannot be observed in practise, which confines empiricists to the use of discretely sampled prices and Δ-period high frequency returns are defined as $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$. Adopting the convention of the established literature, without loss of generality the daily time interval is normalized to unity (i.e. Δ=1, implying that $1/\Delta$ measures the number of intraday intervals) and, for ease of notation, daily returns are labelled by a single time subscript, such that $r_{t+1} \equiv r_{t+1,1}$, a notation that is transferable to all subsequent daily time series. The daily realised variation is then defined as the summation of the corresponding $1/\Delta$ high frequency intraday squared returns,

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r_{t+j\cdot\Delta,\Delta}^2 , \tag{4.2}$$

where $1/\Delta$ is assumed to be an integer. The daily realised volatility is then defined strictly as the square root of the realised variation, although it is common for both terms to be used interchangeably when referring to the realised variation defined in equation (4.2). The important implication of this measure, as first emphasised by Andersen and Bollerslev (1998b), Andersen, Bollerslev, Diebold and Labys (2001), Barndorff-Nielsen and Shephard (2002a, b) and Comte and Renault (1998), is that, as the sampling frequency of the underlying returns increases, the realised variation converges uniformly in probability to the increment of the quadratic variation process, a result which has provided the theoretical cornerstone for the vast realised volatility literature that has emerged recently. Specifically, for $\Delta \to 0$:

$$RV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(s)ds + \sum_{t<s\leq t+1} \kappa^2(s) . \tag{4.5}$$

In the absence of jumps, as considered in the earlier studies, realised variation as defined in equation (4.2) is a consistent estimator for the integrated volatility. The overwhelming empirical evidence for the presence of jumps presented more recently, however, motivates the inclusion of the additional contribution of jumps in the continuous-time model of the log-price process to provide a more accurate understanding of total price variation. The immense benefit of equation (4.5) is that the only requirement for a consistent estimator of total price variation is high frequency data, making this an entirely non-parametric measurement approach. Extending the theory of realised variation, whilst also incorporating discontinuous jumps in the price process, Barndorff-Nielsen and Shephard (2003, 2004b) have developed a more general framework by presenting asymptotic results for realised power variation, which is defined as

$$RPV_{t+1}(\Delta, p) \equiv \Delta^{1-p/2} \mu_p^{-1} \sum_{j=1}^{1/\Delta} \left| r_{t+j\cdot\Delta,\Delta} \right|^p, \tag{4.6}$$

where $\mu_p \equiv 2^{p/2} \Gamma(\frac{1}{2}(p+1)) / \Gamma(\frac{1}{2}) = E\left(|Z|^p\right)$ and Z is a standard normally distributed random variable. Furthermore, Barndorff-Nielsen and Shephard (2003, 2004b) show that for $\Delta \to 0$ and $0<p<2$

$$RPV_{t+1}(\Delta, p) \to \int_t^{t+1} \sigma^p(s) ds. \tag{4.13}$$

The choice of p is crucial to this result. Equation (4.13) reveals that for power variation measures with $0<p<2$, the impact of the discontinuous jumps disappears in the limit as $\Delta \to 0$. For $p>2$, realised power variation diverges to infinity, while for $p=2$ the realised power variation is identical to the realised variation measure of equation (4.2), which, in the limit, converges to integrated volatility plus the sum of squared jumps as in equation (4.5).

The most influential developments in the theory of realised power variation for the identification of jumps are the definition, and the powerful and robust asymptotic result (for $\Delta \to 0$), provided by Barndorff-Nielsen and Shephard (2004b) for realised bipower variation, which allows the separation of the continuous and discontinuous components of quadratic variation. Specifically, standardised realised bipower variation is defined as the scaled summation of the product of adjacent absolute high frequency returns,

$$BV_{t+1}(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} \left| r_{t+j\cdot\Delta,\Delta} \right| \left| r_{t+(j-1)\cdot\Delta,\Delta} \right|, \tag{4.7}$$

where $\mu_1 \equiv \sqrt{2/\pi} = E(|Z|)$. Importantly, Barndorff-Nielsen and Shephard (2004b) show that realised bipower variation converges in the limit (as $\Delta \rightarrow 0$) to integrated volatility:

$$BV_{t+1}(\Delta) \rightarrow \int_t^{t+1} \sigma^2(s)ds. \tag{4.14}$$

More intuitively, as noted by Andersen, Bollerslev, Frederiksen and Nielsen (2006), for small values of Δ, there will be at most one jump in any short sampling interval and hence the product of two adjacent high frequency absolute returns will be unaffected by jumps. The diffusive volatility, however, will remain approximately constant over any two adjacent time intervals, so that the scaled product of the adjacent absolute returns will approximate the squared returns. Combining the results of equations (4.5) and (4.14) then allows the contribution to the quadratic variation process due to the jumps to be isolated and consistently estimated (for $\Delta \rightarrow 0$) as the difference between realised variation and realised bipower variation,

$$RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \rightarrow \sum_{t<s\leq t+1} \kappa^2(s). \tag{4.8}$$

This insight has created the framework for numerous recent studies focusing on the separate components of quadratic variation and jumps, including Andersen, Bollerslev and Diebold (2007b), Barndorff-Nielsen and Shephard (2006) and Huang and Tauchen (2005), and forms the basis of this study into the impact of macroeconomic news in determining jumps. Additionally, in a more practical setting any given sample of discrete returns is clearly finite (Δ>0) and the difference between the realised variation and realised bipower variation may provide negative estimates for the contribution of squared jumps. To prevent such theoretically infeasible estimates and following the recent literature, empirical applications of equation (4.8) are truncated at zero,

$$J_{t+1}(\Delta) \equiv \max\left[RV_{t+1}(\Delta) - BV_{t+1}(\Delta), 0\right], \tag{4.15}$$

ensuring that the contribution of jumps to daily quadratic variation is identified as non-negative.

4.3.3 Asymptotic Theory and Significant Jumps

The method described in the previous sub-section identifies jumps as the difference between realised variation and bipower variation, the theoretical background for which relies on sampling returns at ever higher frequencies until, in the limit, $\Delta \to 0$. An empirical application of this technique, however, implies the use of a fixed sampling frequency (Δ>0), which may induce some finite sample measurement error. The non-negative truncation in equation (4.15) helps to solve this problem by discarding theoretically infeasible negative estimates for the squared jumps. However, as Andersen, Bollerslev and Diebold (2007b) note, a related complication may manifest itself as the resulting time series of jump contributions containing an unreasonably large number of non-zero small positive values. Although identified as discontinuities these small jumps may be measurement errors, which should be attributed to the continuous sample path variation process. This sub-section documents the theoretical framework for implementing a shrinkage estimation procedure that identifies only significant jumps, thereby associating only sufficiently large values of $RV_{t+1}(\Delta) - BV_{t+1}(\Delta)$ with the jump component.

The asymptotic distribution theory developed in Barndorff-Nielsen and Shephard (2004b, 2006) states that, for $\Delta \to 0$,

$$\Delta^{-1/2} \frac{RV_{t+1}(\Delta) - BV_{t+1}(\Delta)}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)\int_t^{t+1} \sigma^4(s)ds\right]^{1/2}} \to N(0,1), \tag{4.16}$$

which holds under sufficient regularity, frictionless market conditions and in the absence of jumps. The interpretation of this result implies that a significant jump occurs during the time interval $[t,\ t+1]$ if the standardised difference between $RV_{t+1}(\Delta)$ and $BV_{t+1}(\Delta)$ is particularly large. Integrated quarticity, $\int_t^{t+1}\sigma^4(s)ds$, is latent and so requires estimation in order for the appropriate standardisation in equation (4.16) to be implemented. Two alternative estimators have been advocated in the recent literature. Barndorff-Nielsen and Shephard (2004b, 2006) propose the robust realised quadpower quarticity measure,

$$QQ_{t+1}(\Delta) \equiv \Delta^{-1}\mu_1^{-4}\sum_{j=4}^{1/\Delta}\left|r_{t+j\cdot\Delta,\Delta}\right|\left|r_{t+(j-1)\cdot\Delta,\Delta}\right|\left|r_{t+(j-2)\cdot\Delta,\Delta}\right|\left|r_{t+(j-3)\cdot\Delta,\Delta}\right|, \tag{4.17}$$

which has the following asymptotic property, as $\Delta \to 0$:

$$QQ_{t+1}(\Delta) \to \int_t^{t+1}\sigma^4(s)ds, \tag{4.18}$$

making it a consistent estimator for integrated quarticity, a property which also holds in the presence of jumps. As an extension to the theory underlying the use of realised bipower variation for the robust and consistent estimation of the integrated volatility, Andersen, Bollerslev and Diebold (2007b) opt instead to use tripower quarticity as a consistent estimator of integrated quarticity. This is defined as the normalised sum of the product of $n \geq 3$ adjacent absolute returns raised to the power of $4/n$. Specifically, for the case where n=3,

$$TQ_{t+1}(\Delta) \equiv \Delta^{-1}\mu_{4/3}^{-3}\sum_{j=3}^{1/\Delta}\left|r_{t+j\cdot\Delta,\Delta}\right|^{4/3}\left|r_{t+(j-1)\cdot\Delta,\Delta}\right|^{4/3}\left|r_{t+(j-2)\cdot\Delta,\Delta}\right|^{4/3}, \tag{4.19}$$

where $\mu_{4/3} \equiv 2^{2/3}\cdot\Gamma(7/6)\cdot\Gamma(1/2)^{-1} = E\left(|Z|^{4/3}\right)$ and it is possible to show that even in the presence of jumps, for $\Delta \to 0$,

$$TQ_{t+1}(\Delta) \rightarrow \int_{t}^{t+1} \sigma^4(s)ds. \tag{4.20}$$

Equations (4.16)-(4.20) imply that important jumps can be identified by calculating the empirical realisations of the following alternative feasible statistics:

$$W_{t+1}(\Delta)_{QQ} \equiv \Delta^{-1/2} \frac{RV_{t+1}(\Delta) - BV_{t+1}(\Delta)}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)QQ_{t+1}(\Delta)\right]^{1/2}}, \tag{4.21}$$

$$W_{t+1}(\Delta)_{TQ} \equiv \Delta^{-1/2} \frac{RV_{t+1}(\Delta) - BV_{t+1}(\Delta)}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)TQ_{t+1}(\Delta)\right]^{1/2}}, \tag{4.22}$$

against a standard normal distribution. Recent evidence presented by Huang and Tauchen (2005) reveals that the choice between $QQ_{t+1}(\Delta)$ and $TQ_{t+1}(\Delta)$ is not important for the performance of the statistical test. For this reason, and in order to maintain consistency with the recent literature, the remaining explanations are based only on test statistics using $TQ_{t+1}(\Delta)$ as the estimator of integrated quarticity; however, it is important to note that this could be replaced with $QQ_{t+1}(\Delta)$ without loss of generality.

The recent study of Huang and Tauchen (2005) compares the finite sample performance of alternative versions of this test statistic in a comprehensive simulation based exercise. The versions of the test statistic are represented as

$$W_{t+1}(\Delta) \equiv \Delta^{-1/2} \frac{RV_{t+1}(\Delta) - BV_{t+1}(\Delta)}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)TQ_{t+1}(\Delta)\right]^{1/2}}, \tag{4.22}$$

$$W_{t+1}(\Delta)_{l} \equiv \Delta^{-1/2} \frac{\log\left(RV_{t+1}(\Delta)\right) - \log\left(BV_{t+1}(\Delta)\right)}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)TQ_{t+1}(\Delta)BV_{t+1}(\Delta)^{-2}\right]^{1/2}}, \tag{4.23}$$

$$W_{t+1}(\Delta)_{l,m} \equiv \Delta^{-1/2} \frac{\log\left(RV_{t+1}(\Delta)\right) - \log\left(BV_{t+1}(\Delta)\right)}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)\max\left\{1, TQ_{t+1}(\Delta)BV_{t+1}(\Delta)^{-2}\right\}\right]^{1/2}}. \tag{4.24}$$

Equation (4.22) is the standard linear version of the test, which exhibits a size distortion towards over rejecting the null hypothesis of no jumps in the right hand tail at conventional significance levels. The logarithmic transformation of Huang and Tauchen (2005), denoted by the subscript l in equation (4.23), and the maximum value adjustment of Barndorff-Nielsen and Shephard (2004b), denoted by the subscript m in equation (4.24), improve the finite sample performance of the test. In addition to the linear jump test, Huang and Tauchen (2005) also present the following alternative ratio jump tests to investigate the relative contribution of jumps to total price variation:

$$W_{t+1}(\Delta)_r \equiv \Delta^{-1/2} \frac{\left[RV_{t+1}(\Delta) - BV_{t+1}(\Delta)\right]RV_{t+1}(\Delta)^{-1}}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)TQ_{t+1}(\Delta)BV_{t+1}(\Delta)^{-2}\right]^{1/2}}, \tag{4.25}$$

$$W_{t+1}(\Delta)_{r,m} \equiv \Delta^{-1/2} \frac{\left[RV_{t+1}(\Delta) - BV_{t+1}(\Delta)\right]RV_{t+1}(\Delta)^{-1}}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)\max\left\{1, TQ_{t+1}(\Delta)BV_{t+1}(\Delta)^{-2}\right\}\right]^{1/2}}, \tag{4.26}$$

where the subscript r denotes the ratio version of these tests. Huang and Tauchen (2005) eventually settle on equation (4.26) as their preferred approach and this version has been implemented in the empirical work of Andersen, Bollerslev and Diebold (2007b). Equation (4.23) has also been employed recently by Andersen, Bollerslev, Frederiksen and Nielsen (2006). In order to investigate the relative jump detection performance of alternative specifications for the jump test statistic, to maintain comparability with the most recent literature, and to simplify the notation, this study performs the following daily jump tests:[17]

$$W_{t+1}(\Delta) \equiv \Delta^{-1/2} \frac{RV_{t+1}(\Delta) - BV_{t+1}(\Delta)}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)TQ_{t+1}(\Delta)\right]^{1/2}}, \tag{4.27}$$

$$Z_{t+1}(\Delta) \equiv \Delta^{-1/2} \frac{\left[RV_{t+1}(\Delta) - BV_{t+1}(\Delta)\right]RV_{t+1}(\Delta)^{-1}}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)\max\left\{1, TQ_{t+1}(\Delta)BV_{t+1}(\Delta)^{-2}\right\}\right]^{1/2}}, \tag{4.28}$$

[17] These equations simply highlight the relevant test statistics used in this study and clarify their notation.

$$U_{t+1}(\Delta) \equiv \Delta^{-1/2} \frac{\log(RV_{t+1}(\Delta)) - \log(BV_{t+1}(\Delta))}{\left[(\mu_1^{-4} + 2\mu_1^{-2} - 5) TQ_{t+1}(\Delta) BV_{t+1}(\Delta)^{-2}\right]^{1/2}}, \tag{4.29}$$

Significant jumps are identified by the realisations of $W_{t+1}(\Delta)$, $Z_{t+1}(\Delta)$ and $U_{t+1}(\Delta)$ in excess of an appropriate critical value, $\Phi_{1-\alpha}$:

$$J_{t+1,\alpha}(\Delta)(W) \equiv I[W_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)],$$

$$J_{t+1,\alpha}(\Delta)(W) \equiv I[W_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)], \tag{4.30a}$$

$$J_{t+1,\alpha}(\Delta)(Z) \equiv I[Z_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)], \tag{4.30b}$$

$$J_{t+1,\alpha}(\Delta)(U) \equiv I[U_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)], \tag{4.30c}$$

where $I[\cdot]$ denotes an indicator function. The corresponding estimate(s) of the continuous sample path component variation must therefore be

$$C_{t+1,\alpha}(\Delta)(W) \equiv I[W_{t+1}(\Delta) \leq \Phi_{1-\alpha}] \cdot RV_{t+1}(\Delta) + I[W_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot BV_{t+1}(\Delta), \tag{4.31a}$$

$$C_{t+1,\alpha}(\Delta)(Z) \equiv I[Z_{t+1}(\Delta) \leq \Phi_{1-\alpha}] \cdot RV_{t+1}(\Delta) + I[Z_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot BV_{t+1}(\Delta), \tag{4.31b}$$

$$C_{t+1,\alpha}(\Delta)(U) \equiv I[U_{t+1}(\Delta) \leq \Phi_{1-\alpha}] \cdot RV_{t+1}(\Delta) + I[U_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot BV_{t+1}(\Delta), \tag{4.31c}$$

in order to ensure that the sum of the jump variation and continuous sample path component variation are equal to the total realised variation. Importantly, both $J_{t+1,\alpha}(\Delta)$ and $C_{t+1,\alpha}(\Delta)$ in equations (4.30) and (4.31) are guaranteed to be positive with the use of the condition $\Phi_{1-\alpha} > 0$, for appropriate values of α. Analogously, the non-negativity truncation represented in equation (4.15) implicitly assumes $\alpha = 0.5$.

4.3.4 Market Microstructure Noise

Discrete price grid points, bid-ask spreads and non-synchronous trading, are some of the market microstructure frictions that not only preclude a continuum of prices from being observed, but also invalidate the assumption that a continuously observed logarithmic price process follows a semi-martingale.[18] More realistically, therefore, following Andersen, Bollerslev and Diebold (2007b), Andersen, Bollerslev and Dobrev (2007), Aït-Sahalia, Mykland and Zhang (2005), Bandi and Russell (2006), Huang and Tauchen (2995), and Zhang, Mykland and Aït-Sahalia (2005), the observed price process is defined as $p(t) = p^*(t) + v(t)$, such that the true (latent) semi-martingale logarithmic price process that would obtain in the absence of any frictions, $p^*(t)$, is contaminated by the *i.i.d.* white noise component, $v(t)$. The observed returns, which are sampled discretely every Δ period, are then calculated as

$$r_{t,\Delta} \equiv p^*(t) - p^*(t-\Delta) + v(t) - v(t-\Delta) \equiv r^*_{t,\Delta} + \eta_{t,\Delta}, \qquad (4.32)$$

which are equal to the true (latent) returns plus a first-order moving average process, $\eta_{t,\Delta}$. The first complication arising from the presence of noise of this structure, as discussed by Andersen, Bollerslev and Diebold (2007b) and Huang and Tauchen (2005), is that the noise term will bias the measurement of $RV_{t+1}(\Delta)$ in equation (4.2), the noise term dominating as $\Delta \to 0$, meaning that $RV_{t+1}(\Delta)$ is no longer consistent as an estimate of the quadratic variation of $p^*(t)$. This bias is most easily controlled for in practical applications by an appropriate choice of the sampling frequency, the selection of which can be guided by volatility signature plots, which plot sample averages of $RV_{t+1}(\Delta)$ against the sampling frequency, Δ. Many recent studies report that this bias in the realised variation measure appears to disappear at the five-minute sampling frequency.

Second, in considering bipower variation, Andersen, Bollerslev and Diebold (2007b) and Huang and Tauchen (2005) note that the market microstructure noise term induces an upward bias in $BV_{t+1}(\Delta)$, defined in equation (4.7), which is also controlled by the appropriate choice of Δ. However, the symptomatic first order serial correlation in $\eta_{t,\Delta}$ also generates serial dependence between any two adjacent observed returns, say $r_{t+j\cdot\Delta,\Delta}$ and $r_{t+(j-1)\cdot\Delta,\Delta}$. As Andersen, Bollerslev and Diebold (2007b) note, the presence of *i.i.d* noise generates spurious first order serial

[18] See also Neftci (2007) for further arguments that these effects may be caused by 'barrier', 'stop loss' and 'spread' trading.

correlation, which presents an additional source of bias for realised bipower variation and also applies analogously to the adjacent returns used in the calculation of tripower quarticity in equation (4.19). Consequently, and of critical importance to this empirical work, Huang and Tauchen (2005) show that the presence of market microstructure noise biases the jump test statistics against finding jumps. As a possible remedy, the spurious serial correlation in the observed returns, defined in equation (4.32), is annihilated by using staggered returns rather than adjacent returns. Specifically, the staggered realised bipower variation measure may be represented as

$$BV_{1,t+1}(\Delta) \equiv \mu_1^{-2}(1-2\Delta)^{-1}\sum_{j=3}^{1/\Delta}\left|r_{t+j\cdot\Delta,\Delta}\right|\left|r_{t+(j-2)\cdot\Delta,\Delta}\right|, \tag{4.33}$$

which substitutes the absolute adjacent returns in equation (4.7) with the corresponding one interval staggered absolute returns. $(1-2\Delta)^{-1}$ is a normalisation factor included to account for the loss of two observations due to the one interval staggering. Similarly, the one interval staggered realised tripower quarticity measure is given by

$$TQ_{1,t+1}(\Delta) \equiv \Delta^{-1}\mu_{4/3}^{-3}(1-4\Delta)^{-1}\sum_{j=5}^{1/\Delta}\left|r_{t+j\cdot\Delta,\Delta}\right|^{4/3}\left|r_{t+(j-2)\cdot\Delta,\Delta}\right|^{4/3}\left|r_{t+(j-4)\cdot\Delta,\Delta}\right|^{4/3}. \tag{4.34}$$

Higher order serial dependence could be overcome by increasing the lag length, but this would involve the loss of yet more observations due to the greater staggering. Importantly, the staggered realised variation measures presented in equations (4.33) and (4.34) are consistent for the integrated variation and integrated quarticity, respectively, even in the absence of the market microstructure noise contamination, a result shown by Barndorff-Nielsen and Shephard (2004b). Finally, with regard to the jump test statistics, the asymptotic distribution (for $\Delta \to 0$) of the test statistics calculated using the modified one interval staggered realised variation measures, $BV_{1,t+1}(\Delta)$ and $TQ_{1,t+1}(\Delta)$, rather than $BV_{t+1}(\Delta)$ and $TQ_{t+1}(\Delta)$ in equations (4.27)-(4.29), will be asymptotically standard normally distributed. In empirical applications relying on finite samples, more accurate finite sample approximations should be obtained when using staggered versions of realised bipower variation and tripower quarticity, as suggested by the simulation evidence of Huang and Tauchen (2005), since the staggering should help to eliminate the influences of the market microstructure noise for these measures. This chapter focuses on these staggered versions of the tests, however, for completeness and comparability, all tests are performed using the original versions and important differences in results are noted where necessary.

4.3.5 Intraday Jump Identification

Even after accounting for market microstructure noise, current jump identification techniques are only able to isolate the trading days that contain at least one jump. Given that these techniques rely on high frequency asset returns and that this chapter intends to examine the possible relationships between news announcements and jumps, it is essential to be able to identify the precise intraday intervals during which these jumps occur and detect possible multiple jumps on a particular day. This sub-section demonstrates alternative intraday jump detection techniques that have been proposed in the most recent literature.

The first technique is presented by Andersen, Bollerslev and Dobrev (2007) as part of their investigation of the importance of leverage effects, jumps and *i.i.d* noise for the ability of continuous-time jump-diffusion models to describe observed asset return distributions. Andersen, Bollerslev and Dobrev (2007) note that the distributional results for the pure diffusion case break down in the presence of a jump component and, as a potential solution, their intraday jump detection technique aims to provide a jump-adjusted asset price path so that distributional implications may be tested against the pure diffusive benchmark. This identification technique applies a uniform decision rule to compare individual intraday absolute returns against an appropriately scaled realisation of bipower variation, which is robust to jumps, thus allowing the identification of multiple significant jumps on each trading day. Specifically, Andersen, Bollerslev and Dodrev (2006) define $r_{t+\xi\cdot\Delta,\Delta}=\sum_{j=1}^{1/\Delta} r_{t+j\cdot\Delta,\Delta} I(\xi=j)$, where ξ is an independently drawn index (uniformly distributed) from the set $\{1,2,\ldots,1/\Delta\}$, and so a randomly selected intraday return. They then and consider whether this return is subject to a jump by comparing its absolute value to an appropriately scaled realisation of bipower variation. In addition, assuming for tractability that volatility is constant within the trading day, Andersen, Bollerslev and Dobrev (2007) show that individual intraday scaled returns are distributed as

$$\Delta^{-1/2} r_{t+\xi\cdot\Delta,\Delta} \sim N(0, IV_{t+1}), \tag{4.35}$$

a condition that forms the basis for their intraday jump test.

The formal intraday jump detection procedure involves two stages. The first stage selects α, which denotes the size of the daily jump test as described in subsection 4.3.3. The size of the corresponding confidence interval for a randomly drawn intraday diffusive return is then given by $(1-\beta)$, where $\beta = 1-(1-\alpha)^{\Delta}$ defines the corresponding level of the intraday jump test. Using realised bipower variation to estimate daily integrated volatility, randomly drawn intraday diffusive returns are distributed approximately as $N\left(0, \Delta \cdot BV_{t+1}(\Delta)\right)$ so that possible multiple intraday jumps during interval k, $\kappa_k(\Delta)$, are then detected by

$$\kappa_k(\Delta) = r_{t+k\cdot\Delta,\Delta} \cdot I\left[\left|r_{t+k\cdot\Delta,\Delta}\right| > \Phi_{1-\beta/2} \cdot \sqrt{\Delta \cdot BV_{t+1}(\Delta)}\right], \qquad k = 1,2,\ldots,\frac{1}{\Delta}, \tag{4.36}$$

where $\Phi_{1-\beta/2}$ refers to the corresponding critical value from the standard normal distribution. The assumption that volatility is constant within a trading day deserves further mention, particularly in light of the overwhelming evidence for the presence of intraday volatility patterns provided in the previous chapter. Whilst Andersen, Bollerslev and Dobrev (2007) recognise that this procedure will tend to over-reject the null hypothesis of a pure diffusion process in the presence of substantial intraday variation in volatility, this can be addressed by choosing conservative values for α and hence β. Andersen, Bollerslev and Dobrev (2007) also provide simulation evidence showing that this intraday jump detection procedure performs well for a variety of jump-diffusion specifications that include intraday time-variation in volatility. This intraday jump detection test is also found to uniformly dominate the prevailing daily jump tests, which are based on the discrepancy between realised volatility and bipower variation over each trading day, in terms of size, power and jump identification capability. Furthermore, Andersen, Bollerlev and Dobrev (2007) show that accounting for intraday volatility patterns in empirical data by standardising intraday returns by the average sample standard deviation for each corresponding intraday interval does not impact their basic conclusions. This chapter aims to investigate this issue explicitly by comparing the implementation of this intraday jump detection procedure on raw returns with returns standardised (crudely) by both average absolute returns and standard deviation as measures of the intraday volatility pattern. Market microstructure frictions remain an issue in this test and the jump detection procedure is conducted on staggered measures of realised bipower variation as explained in section 4.3.4.

A second and alternative approach has been advocated recently by Andersen, Bollerslev, Frederiksen and Nielsen (2006), whose sequential jump detection procedure is also designed to identify all of the jumps, along with their exact times, within a particular day. Specifically, this technique identifies significant jumps sequentially through calculating the difference between the largest squared intraday returns during days containing at least one jump and the average of the remaining (non-jump) intraday squared returns. Intuitively, in the absence of jumps, the average contribution of each squared intraday return to the continuous sample path component is simply $\Delta \cdot \sum_{j=1}^{1/\Delta} r_{t+j\cdot\Delta,\Delta}^2$. Following Andersen, Bollerslev, Frederiksen and Nielsen (2006), and assuming only a single jump on a particular day, the contribution to total volatility arising from the jump is estimated by:

$$\widetilde{JV}_{t,k}(\Delta) = I[W_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot \left(\max r_{t+j\cdot\Delta,\Delta}^2 - \frac{\Delta}{1-\Delta} \sum_{j=1, j\neq k}^{1/\Delta} r_{t+j\cdot\Delta,\Delta}^2 \right), \qquad (4.37a)$$

$$\widetilde{JV}_{t,k}(\Delta) = I[Z_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot \left(\max r_{t+j\cdot\Delta,\Delta}^2 - \frac{\Delta}{1-\Delta} \sum_{j=1, j\neq k}^{1/\Delta} r_{t+j\cdot\Delta,\Delta}^2 \right), \qquad (4.37b)$$

$$\widetilde{JV}_{t,k}(\Delta) = I[U_{t+1}(\Delta) > \Phi_{1-\alpha}] \cdot \left(\max r_{t+j\cdot\Delta,\Delta}^2 - \frac{\Delta}{1-\Delta} \sum_{j=1, j\neq k}^{1/\Delta} r_{t+j\cdot\Delta,\Delta}^2 \right), \qquad (4.37c)$$

where $I[\cdot]$ is an indicator function and k denotes the precise intraday interval containing the jump. The corresponding return during interval k indicates the direction of the jump and measures its magnitude:

$$\widetilde{\kappa}_k(\Delta) = r_{t+k\cdot\Delta,\Delta} \,. \qquad (4.38)$$

The sequential detection of numerous jumps during a particular day occurs as follows. First, the realised variation, $RV_{t+1}(\Delta)$, is calculated as the summation of all the squared intraday returns according to equation (4.8). If the daily jump test, $W_{t+1}(\Delta)$, $Z_{t+1}(\Delta)$ or $U_{t+1}(\Delta)$ rejects the null hypothesis that there are no jumps, at least one jump is identified during this day and the contribution of the jump to total daily variation is measured as the difference between the largest squared intraday return and the average of the remaining $(1/\Delta - 1)$ squared returns. To identify a second possible jump, Andersen, Bollerslev, Frederiksen and Nielsen (2006) correct $RV_{t+1}(\Delta)$ for the first jump by re-calculating it as the summation of squared intraday returns where the squared return containing the first jump is replaced by the average of the remaining $(1/\Delta - 1)$ squared returns, which exclude this first jump. The daily jump test statistic, $W_{t+1}(\Delta)$, $Z_{t+1}(\Delta)$ or $U_{t+1}(\Delta)$, is re-calculated by replacing $RV_{t+1}(\Delta)$ with the corresponding jump-adjusted realised variation measure. If this second test does not reject the null, there is evidence of exactly one jump on this particular day and the sequential procedure is stopped. If the second test rejects again, there are at least two jumps, and the contribution of the second jump is calculated as the second largest squared return, less the average of the remaining $(1/\Delta - 2)$ squared returns that exclude both intraday jumps. Realised volatility for this day is then adjusted for the second jump, by replacing the second largest squared return with the average of the remaining squared returns and the sequence continues until the corresponding daily jump test no longer rejects. This sequential method is employed in this chapter by replacing standard measures of realised bipower variation and tripower quarticity with their staggered counterparts in order to annihilate the effects of market microstructure noise.

4.4 EMPIRICAL RESULTS

4.4.1 Data

In order to conduct a thorough analysis of the identification of jumps, this study applies the daily and intradaily jump detection procedures detailed above to asset markets across geographic locations and asset classes over an eight-year period.

More specifically, this chapter uses high frequency returns for three foreign exchange, stock index and bond futures contracts from the US, UK and Europe. This section reports the basic information and sources of this data along with some of its salient features.

As documented by Andersen, Bollerslev, Diebold and Vega (2007), futures markets are particularly instructive for high frequency studies concentrating on abrupt price movements for a number of reasons. First, tick data relating to futures contracts are readily available and report transaction prices, which are more useful than indicative quotes.[19] Second, futures markets involve much lower transactions costs than their corresponding cash markets, ensuring that the contracts selected for this study are very actively traded. In relation to this, there is also evidence that futures markets generally lead the cash market in terms of price discovery (Hasbrouck, 2003). Third, in light of the potential for dramatic asset return jumps in response to the arrival of macroeconomic news, it is of crucial importance for this study that asset markets are open and active at the time of macroeconomic news announcements in order to capture these potential jumps. The futures markets used in this study are selected carefully such that they are active at 8.30 EST when many important US macroeconomic indicators are announced, as compared to other cash and futures markets that are closed at this time.

The sample runs from July 1998 to June 2006 and delivery months for each contract are March, June, September and December. In order to create a continuous series of futures prices, the contract closest to expiration is used, switching to the next-maturity contract automatically when the latter becomes more actively traded. Table 4.4.1.1 provides basic information on the various futures contracts' trading specifications. The Euro-Dollar (EUR-USD), Sterling-Dollar (GBP-USD) and Yen-Dollar (JPY-USD) contracts trading on the Chicago Mercantile Exchange (CME) and the US 10 year Treasury Bond contract trading on the Chicago Board of Trade (CBOT) are open auction, pit traded contracts. However, from July 2003 the data resulting form pit trading within the trading hours specified are augmented by data generated by electronic trading.

[19] The data employed here was obtained from Tick Data Inc.

Table 4.4.1.1. Futures Contracts.

Futures Contract	Exchange	Trading Hours (Local Time)	Trading Hours (EST)	Sample	Days
EUR-USD	CME/Globex	7:20 - 14:00	8:20 - 15:00	01/99 - 06/06	1,819
GBP-USD	CME/Globex	7:20 - 14:00	8:20 - 15:00	07/98 - 06/06	1,938
JPY-USD	CME/Globex	7:20 - 14:00	8:20 - 15:00	07/98 - 06/06	1,939
S&P 500 E-Mini	CME/Globex	7:20 - 15:15	8:20 - 16:15	07/98 - 06/06	1,993
FTSE 100	Euronext.liffe	8:00 - 17:30	3:00 - 12:30	07/98 - 06/06	1,981
DJ Euro Stoxx 50	Eurex	8:50 - 22:00	2:50 - 16:00	01/99 - 06/06	1,901
US 10-Year Treasury Bond	CBOT	7:20 - 14:00	8:20 - 15:00	07/98 - 06/06	1,905
UK Gilt	Euronext.liffe	8:00 - 18:00	3:00 - 13:00	07/98 - 06/06	1,969
Euro Bund	Eurex	8:00 - 22:00	2:00 - 16:00	07/98 - 06/06	2,022

Notes: Data from CME is supplemented by electronic trading from Globex during the trading hours specified, from July 2003 onwards. UK futures contracts traded on the London International Financial Futures and Options Exchange (LIFFE) before the exchange was acquired in January 2002 by Euronext, forming Euronext.liffe. Trading hours on Euronext.liffe and Eurex represent those currently in operation and details of extensions to trading hours are provided in the text. The final column shows the number of full trading days available for each contract in the sample after removing days due to holidays and missing data.

Although electronic trading and therefore futures data for these contracts are available beyond these trading hours, the pit opening times are maintained in this study to maintain consistency over the entire sample and because electronic trading volumes tend to be very low outside the pit trading sessions. The remaining contracts, namely the FTSE 100, DJ Euro Stoxx 50, UK Gilt and Euro Bund, are all traded electronically under strict opening hours. The S&P 500 E-Mini contract has different specifications, being traded electronically between the hours of 16:30 and 16:15 EST.[20] The S&P 500 E-Mini contract is chosen to represent the US stock market in preference to the S&P 500 index future because it is actively traded at the time of important macroeconomic announcements at 8:30 EST, whereas trading in the S&P 500 index future begins later at 9:30 EST. In addition, the smaller size of the S&P 500 E-Mini contract makes it more accessible to a wider range of investors than the standard S&P 500 index future, thereby making it highly liquid. In general, the period of the trading day demonstrating most liquidity for the S&P 500 E-Mini contract coincides with the opening times of the contracts traded on CME and CBOT, but extending slightly from 15:00 to 16:15 EST, even though the contract can be traded during longer hours. At 16.15 EST trading in the S&P 500 E-Mini closes for fifteen minutes providing a natural end to the day's trading activity. Guided by these times of liquidity, this study applies trading hours of 8:20 to 16:15 EST for this contract.

The trading hours listed in Table 4.4.1.1 for the FTSE 100, Bund and DJ Euro Stoxx 50 contracts represent those currently (at the time of writing) specified by the respective exchanges, but trading hours have been extended during this sample. Throughout this study, data on these futures contracts include all available opening hours offering sufficient trading activity.[21] Data on the EUR-USD foreign exchange contract is unavailable before the inception of the Euro in January 1999, and, although futures data is available for the DJ Euro Stoxx 50 index futures from July to December 1998, the trading volume is very low during this period and is therefore

[20] Prior to 07/03, the S&P 500 E-Mini could be traded in the hours 00:00 to 15:15.

[21] Specifically, this study uses opening hours of 8:45 to 17:30 from 01/07/98 to 17/09/99 and 8:00 to 17:30 from 20/09/99 to 30/06/06 for the FTSE 100 contract; of 8:00 to 19:00 during the period 01/07/98 to 18/11/05 and 08:00 to 22:00 between 21/11/05 and 30/06/06 for the Bund contract; and 10:00 to 17:00, extended to 09:00 to 17:00 on 18/10/99, extended to 09:00 to 17:30 on 24/01/00, extended to 09:00 to 20:00 on 02/01/02, extended to 08:50 to 20:00 on 21/11/05, and extended to 08:50 to 22:00 on 01/06/06 for the DJ Euro Stoxx 50 contract. Any minor discrepancies between official exchange opening times and those used in this study are caused by the removal of intervals because they include very few or no trades.

removed from the sample. The three bond futures contracts, the US 10-Year Treasury Bond, UK Gilt and Euro Bund are also carefully chosen so that each contract's underlying government bond has ten years to maturity.

The following empirical work is based on local currency continuously compounded returns, which are calculated as $\log(p_t / p_{t-1}) \cdot 100$, where p_t denotes the price of the last trade in the t'th interval. Raw tick data have been obtained from Tick Data Inc., allowing returns to be calculated at any desired intraday frequency. When extracting data at intraday sampling frequencies, the full data set provides the open, high, low and closing prices during high frequency intervals, along with the number of ticks and trading volume (available from July 2003 only). These are important for the calculation of overnight returns. Where markets operate strict opening hours, and in those markets where opening hours are defined in this study according to trading activity, the first return of a trading day, calculated by comparing the first price of the day with the closing price of the previous night, will often be large, reflecting information publicised whilst the market has been closed. To avoid confounding the empirical analysis in this chapter by including such large returns, the opening return of each day is calculated by comparing the closing price of the first interval of the day with the opening price of that interval: $\log(p_{close} / p_{open}) \cdot 100$. Any interval that contains no trades is assigned the price from the previous interval. Given the non-parametric procedures defined in section 4.3, it is essential that data covers full trading days. Days where data are missing, usually occurring when exchanges close early due to public holidays, or very occasionally due to missing data, are therefore removed from the sample. The total number of full trading days used in this sample is shown in the final column of Table 4.4.1.1 for each futures contract.

4.4.2 Realised Volatility Signature Plots

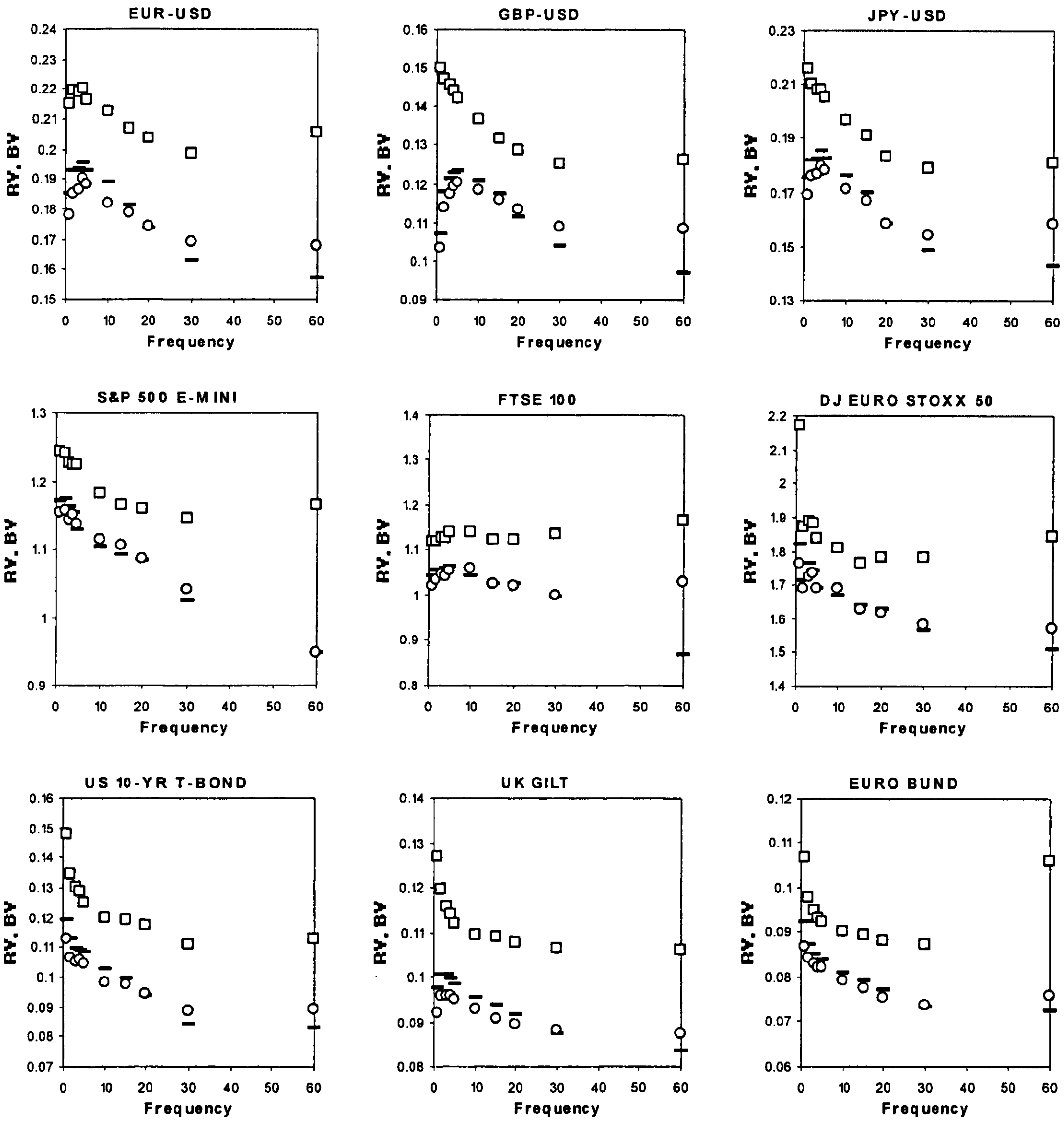
Before implementing jump detection procedures, it is important to select the appropriate sampling frequency for returns, which involves a consideration of the effects of market microstructure frictions. As discussed in section 4.3.4, there exists a tradeoff in selecting the appropriate sampling frequency. Whilst it is important to sample at the highest possible frequency to preserve as much information in the data as possible, the presence of market microstructure noise at the highest frequencies renders realised volatility an inconsistent measure of return variation, generates an upwards bias in measures of bipower variation, and biases jump tests against finding jumps. Realised volatility signature plots, displayed in Figure 4.4.2.1, provide a simple framework for detecting the impact of market microstructure frictions by plotting the average sample mean of realised volatility against the sampling frequency (measured in minutes) of the underlying returns and this is shown by the squares in the scatter plots. Specifically, realised volatility is calculated using returns sampled at frequencies of 1, 2, 3, 4, 5, 10, 15, 20, 30, and 60 minutes. As noted by Andersen, Bollerslev, Frederiksen and Nielsen (2006), in the absence of noise, the realised volatilities should all be consistent measures for the same total variation and so the signature plot should start to flatten out at the frequencies where market microstructure frictions cease to have a distorting impact.

Figure 4.4.2.1 also includes sample averages of bipower variation (dashes) and staggered bipower variation (circles) plotted against sampling frequency for two reasons: first to perform a very simple visual test as to whether there are differences between realised volatility and bipower variation that characterise jump variation; and second to assess the extent to which staggered bipower variation annihilates the effects of market microstructure noise. More specifically, under ideal circumstances and in the limit where the sampling frequency approaches zero, the difference between the realised volatility and the bipower variation provides a consistent measure of the total variation due to jumps.

A number of important features emerge from Figure 4.4.2.1. First, since the realised volatility signature plots are measured on different scales for the vertical axes for illustrative purposes, comparison of volatilities across the nine futures markets requires care. Return variation is highest for the stock market futures and the DJ Euro Stoxx 50 futures contract in particular. The foreign exchange futures are the next most volatile contracts, where the EUR-USD and JPY-USD show the most return variation. Total variation is far lower for the foreign exchange markets than the equity contracts. The bond futures are the least volatile of the three asset classes, with the US 10-Year T-Bond futures the most volatile of the three bond contracts.

In considering the effect of market microstructure noise, the realised volatility plots should flatten at frequencies where noise ceases to have an impact. In confirmation of the findings of Andersen, Bollerslev, Diebold and Labys (2000b) for liquid stocks, realised volatility is highest at the highest sampling frequency.

Figure 4.4.2.1. Realised Volatility Signature Plots.



Notes: The graphs show the sample average realised volatility (RV_t), bipower variation (BV_t) and staggered bipower variation ($BV_{1,t}$) plotted against sampling frequency, measured in minutes, for each futures market. Sampling frequencies include 1, 2, 3, 4, 5, 10, 15, 20, 30, and 60 minutes. Squares denote the levels of realised volatility, dashes represent levels of bipower variation and circles show levels of staggered realised bipower variation. Vertical axes vary between markets for illustrative purposes only.

The presence of negative serial correlation in returns for such liquid futures contracts caused by market microstructure noise helps to explain why this is the case. At lower frequencies, returns are aggregated across longer intervals when calculating realised volatility and oscillating swings in returns tend to cancel each other out generating lower measures of volatility. At the higher frequencies, negatively serially correlated returns are isolated producing higher measures of volatility. As the sampling frequency lengthens, the impact of market microstructure influences decline and realised volatility measures drop until they flatten out at the thirty-minute sampling frequency. The realised volatility signature plots suggest therefore that market microstructure frictions cease to impact on realised volatility at this thirty-minute frequency. This is particularly evident for the three foreign exchange contracts, whereas Figure 4.1.2.1 reveals evidence that the realised volatility plot for all equity index and bond futures contracts flatten at the ten-minute frequency, and at the five-minute frequency for the FTSE 100 and DJ Euro Stoxx 50 futures markets. According to the realised volatility measures, the appropriate sampling frequency varies across markets and asset classes.

As discussed in section 4.3.4, market microstructure noise should impart an upwards bias in measures of bipower variation. This effect can be investigated by considering the pattern of the sample average bipower variation (dashes) in Figure 4.4.2.1. For the foreign exchange markets in the top three plots, bipower variation is surprisingly low at the one-minute frequency and then tends to stabilise at frequencies from two to five minutes. Beyond the five-minute intervals, bipower variation declines steadily as the sampling frequency lengthens. This may be a manifestation of the measurement error of using data sampled at coarse intervals. For the equity contracts, bipower variation is measured at a consistent level for frequencies from one to five minutes, with slight variability for the DJ Euro Stoxx 50 contract. The decline in bipower variation at coarser frequencies than four-minute intervals suggests that five-minute sampling may be conservative for these markets. This is supported by the realised volatility measures as they are at stable levels for the finer frequencies. For the bond markets in the bottom three plots, bipower variation stabilises to a consistent measure at the three-minute frequency and then declines steadily for frequencies lower than five minutes. Reinforcing the findings of the foreign exchange and equity futures contracts, the volatility signature plots for bond futures suggest that a sampling frequency between three and five minutes would be appropriate for the measurement of bipower variation. The more conservative five-minute frequency also supports the findings of Bandi and Russell (2006) and is consistent with the previous studies that have used high frequency data for the detection of jumps.

By considering the difference between the patterns for realised volatility and bipower variation, the volatility signature plots of Figure 4.4.2.1 also provide a rudimentary analysis of the presence of jumps in these markets. As the sampling frequency approaches zero, this difference provides a consistent measure of the returns variation due to jumps. Encouragingly, the difference between realised volatility and bipower variation is remarkably stable for each market for frequencies from two to ten minutes. At the very highest frequency, this difference is exaggerated, whilst the two measures steadily diverge as returns are sampled at frequencies lower than ten minutes. In support of the evidence discussed above, sampling frequencies of between two and ten minutes appear appropriate for measuring the contribution of jump variation.

As a final basic investigation of the effect of market microstructure noise, the volatility signature plots of Figure 4.4.2.1 also show the pattern of staggered bipower variation against sampling frequency. The one-period staggered measure is designed to break the first-order serial correlation between adjacent returns, combating the effect of market microstructure noise, which should reduce any upward bias found in the standard bipower variation measure. The plots of staggered bipower variation, indicated by the circles in Figure 4.1.2.1, behave in a very similar way to their standard counterparts and display a number of important features. First, at the highest sampling frequencies, bipower variation is always greater than staggered bipower variation confirming that the staggering helps to alleviate the upward bias caused by market microstructure frictions. Second, measures of staggered bipower variation are remarkably stable at very high frequencies, clustering at two to five-minute frequencies. However, confirming the evidence of the bipower variation measure above, staggered bipower variation is affected at the one-minute frequency and this is shown by the foreign exchange markets in particular, where both bipower variation measures are surprisingly low at this highest frequency. Third, for all markets, the difference between realised volatility and staggered bipower variation measuring the jump component of total variation is very stable at frequencies from two to five minutes, diverging thereafter as the sampling frequency is lowered. Fourth, bipower variation and staggered bipower variation are approximately equal to each other at frequencies of fifteen minutes for the foreign exchange and bond markets (although slightly lower at the twenty minute frequency for the UK Gilt contract), and five minutes for the equity markets. This suggests that market microstructure noise effects in the measurement of bipower variation are prevalent at frequencies higher than these, which are to some extent alleviated by the use of staggered bipower variation measures.

In brief summary, the realised volatility plots contained in Figure 4.4.2.1 reveal some interesting features regarding the calculation of realised variation measures based on returns sampled at different frequencies. Consideration of bipower variation and staggered bipower variation suggests that returns sampled at intervals of two to five minutes are appropriate, but realised volatility plots suggest lower optimal frequencies that vary across asset classes. The empirical work following in the remainder of this chapter selects five minutes as the appropriate sampling frequency for a number of reasons. First, this corresponds to the previous literature that tests for jumps and investigates the effect of news announcements, representing the two strands of research to be intertwined in this study. This five-minute frequency is also supported by the recent studies of Bandi and Russell (2006a, b) and Aït-Sahalia et al. (2005) in the market microstructure literature. Second, and more important, five-minute sampling represents a satisfactory compromise between retaining the accuracy of return variation measures and the influences of market microstructure noise, although this may by a conservative approach for the equity futures market. Third, in recognising that that there may be some residual market microstructure frictions effects present in the data at this frequency, this study advocates the use of staggered bipower variation in testing for jumps in order to fully control for any remaining influences. Finally, of course a more prudent analysis would require the repetition of tests for a range of sampling frequencies, and whilst this may comprise interesting research in its own right, such an extensive study is left for future work and may be open to charges of data-mining.

4.4.3 Summary Statistics

Table 4.4.3.1 shows the summary statistics for five-minute returns for each futures market under consideration in this chapter. The table shows that the average five-minute returns across all futures markets are very low and are indistinguishable from zero at standard significance levels. Standard deviations are large showing that returns fluctuate around this mean. This deviation is highest for equity futures markets, confirming the high variability found in the previous volatility signature plots relative to the other markets. Foreign exchange markets are the next most volatile according to the standard deviations, with bond futures showing the least variation of the three assets. These measures, however, indicate that fluctuations of returns around their zero means are substantial, and are particularly extreme for the equity index futures. Large skewness statistics reveal that the distributions of sample five-minute returns are not symmetric around their means. Positive values for the foreign exchange futures and the S&P 500 E-Mini futures contract suggest a long right-hand tail and a larger proportion of the distribution above the mean of zero, relative to the normal distribution, whilst the negative statistics for bond, FTSE 100 and DJ Euro Stoxx 50 futures show a long left-hand tail and a disproportionate percentage of the distribution below the zero mean.

The huge kurtosis statistics show clearly that the distributions for five-minute futures returns are leptokurtic, meaning that a large proportion of the distribution lies very close on either side of the mean and with a larger proportion of extreme returns in the tails of the distribution as compared to a normal distribution. This is confirmed by the enormous negative five-minute returns displayed for the minimum values and the huge positive returns shown as the maximum values. For all the markets considered, other than the S&P 500 E-Mini contract, the minimum return value is larger than the maximum return value in absolute terms, which may indicate some asymmetric behaviour in returns. Whilst these statistics confirm the descriptions of previous distributions of samples of high frequency returns, they are encouraging for this study in revealing the possible presence of jumps. That is, the large kurtosis statistics and extreme minimum and maximum returns show that there are unusually large returns of either sign, which may correspond to the presence of jumps.

The final two columns of Table 4.4.3.1 hint at the time series properties of five-minute returns. All first-order autocorrelation functions are negative and are significantly less than zero, except for the FTSE 100 contract whose ACF(1) is indistinguishable from zero. Returns, therefore, are negatively related to the previous five-minute return, a property which is commonly found in empirical studies employing high frequency data.

Table 4.4.3.1. Summary Statistics for Five-Minute Returns.

	N	MEAN	STD DEV	SKEW	KURT	MIN	MAX	ACF(1)	LB(10)
EUR-USD	145,520	0.0005	0.052	0.044	17.43	-1.379	0.948	-0.024	178.37
GBP-USD	155,040	0.0004	0.042	0.128	10.90	-0.720	0.749	-0.040	386.86
JPY-USD	155,120	0.0002	0.051	0.148	21.07	-1.111	1.037	-0.048	533.71
S&P 500 E-Mini	189,335	-0.0003	0.113	0.612	49.09	-2.884	5.584	-0.046	437.62
FTSE 100	223,098	-0.0003	0.101	-0.169	18.91	-3.108	1.666	0.001	71.10
DJ Euro Stoxx 50	221,210	-0.0002	0.126	-0.519	34.44	-5.541	2.034	-0.010	120.07
US 10-Yr T-Bond	152,400	0.0001	0.040	-0.280	47.11	-1.457	0.954	-0.032	219.75
UK Gilt	236,280	0.0001	0.031	-0.191	20.04	-0.788	0.618	-0.024	173.35
Euro Bund	272,268	0.0001	0.026	-0.270	18.30	-0.613	0.574	-0.027	288.40

Notes: The table shows the number of observations (N), mean, standard deviation (std dev), skewness (skew), kurtosis (kurt), minimum (min) and maximum (max) summary statistics for the raw five-minute percentage returns for each futures contract. ACF(1) represents the first order autocorrelation function and LB(10) is the Ljung Box test statistic for serial correlation for up to 10 lags.

Significant first-order correlation in returns may also be a manifestation of the presence of remaining market microstructure noise. The Ljung Box test statistics for up to tenth-order serial correlation are also high for each market, indicating that the structure of serial correlation in the futures returns may be more complex than simply first-order.

As a preliminary analysis for the presence of jumps, Tables 4.4.3.2 to 4.4.3.4 display further summary statistics for the daily realised variation, realised volatility, jump variation and jump series. The daily jump variation series, J_t and $J_{1,t}$, measure the jump variation component of total return variation and are measured as the non-negative difference between realised volatility and realised bipower variation as defined by equation (4.15) in section 4.3.2, with the $J_{1,t}$ series calculated using the one period staggered bipower variation measure of equation (4.30) to account for any market microstructure noise effects that may not be eliminated through the selection of the five-minute sampling frequency as appropriate. The square roots of these series measure the actual daily jumps, but since these are assumed to be positive for this preliminary analysis, this is tantamount to measuring the absolute value of the actual daily jumps. The tables also report the total number of observations for each series, the number of days which show a positive jump and the corresponding proportion of days containing jumps. Tables 4.4.3.2 to 4.4.3.4 show summary statistics for the three foreign exchange, equity index and bond futures markets respectively.

The striking feature of each of these tables is the large proportion of days containing jumps, ranging from 69.49% to 88.67% of days, which are entirely consistent with the findings of Andersen, Bollerslev and Diebold (2007b), Huang and Tauchen (2006) and Tauchen and Zhou (2005). According to this simple analysis jumps are prevalent in the futures markets considered here, however, it is important to note that this simplistic empirical application, which effectively sets the statistical significance of the test to 0.5, is likely to incorrectly identify continuous sample path variation as jump variation. It is therefore instructive to consider the contribution of jump variation to realised variation in order to assess the importance of the jumps identified. The proportional contribution of the mean jump variation to the mean realised variation ranges from 0.080 to 0.176 showing that despite being identified in the vast proportions of days, jump variation does not appear to contribute heavily to total return variation.

Table 4.4.3.2. Summary Statistics for Realised Volatility and Daily Jump Series for Foreign Exchange Futures.

EUR-USD							
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,819		1,461	0.8032		1,472	0.8092
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	0.217	0.164	4.07	34.87	0.019	2.409	618.05
$RV_t^{1/2}$	0.443	0.143	1.53	8.35	0.138	1.552	1,137.60
J_t	0.027	0.052	9.12	127.72	0.000	1.006	2.53
$J_t^{1/2}$	0.126	0.104	1.65	10.72	0.000	1.003	11.82
$J_{1,t}$	0.031	0.069	13.62	301.74	0.000	1.844	4.76
$J_{1,t}^{1/2}$	0.134	0.114	1.96	14.50	0.000	1.358	11.26

GBP-USD							
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,938		1,638	0.8452		1,648	0.8504
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	0.142	0.083	2.81	18.47	0.022	0.985	772.65
$RV_t^{1/2}$	0.365	0.096	1.22	6.32	0.150	0.992	1,034.60
J_t	0.020	0.026	4.64	43.52	0.000	0.362	163.88
$J_t^{1/2}$	0.118	0.081	0.66	4.73	0.000	0.602	393.21
$J_{1,t}$	0.023	0.030	5.31	56.32	0.000	0.460	54.56
$J_{1,t}^{1/2}$	0.124	0.086	0.73	5.23	0.000	0.678	172.81

JPY-USD							
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,939		1,543	0.7958		1,596	0.8231
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	0.205	0.290	20.91	640.39	0.015	9.770	862.98
$RV_t^{1/2}$	0.422	0.164	4.09	49.54	0.121	3.126	2,222.40
J_t	0.025	0.056	12.76	262.29	0.000	1.445	141.82
$J_t^{1/2}$	0.120	0.103	1.98	14.18	0.000	1.202	74.68
$J_{1,t}$	0.029	0.068	11.03	175.42	0.000	1.359	82.94
$J_{1,t}^{1/2}$	0.130	0.110	2.30	16.18	0.000	1.166	53.90

Notes: The Table show the mean, standard deviation, skewness, kurtosis, minimum and maximum summary statistics for realised variation (RV_t), jump variation (J_t, $J_{1,t}$) and their square root counterparts for the three foreign exchange futures contracts. LB (10) denotes the Ljung Box test statistic for serial correlation up to 10 lags. The table also shows the number of observations (N(Days)) in each series and the number of days containing a jump ($N(J_t^+)$, $N(J_{1,t}^+)$). $J_{1,t}$ refers to jump series calculated using the one interval staggered measure of bipower variation.

Table 4.4.3.3. Summary Statistics for Daily Realised Volatility and Jump Series for Equity Index Futures.

	S&P 500 E-Mini						
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,993		1,526	0.7657		1,385	0.6949
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	1.223	1.700	9.93	193.33	0.080	42.552	2,819.70
$RV_t^{1/2}$	0.993	0.488	2.39	16.08	0.283	6.523	7,714.60
J_t	0.113	0.357	19.16	506.27	0.000	11.054	45.96
$J_t^{1/2}$	0.240	0.235	2.92	26.76	0.000	3.325	225.81
$J_{1,t}$	0.116	0.837	37.51	1,554.23	0.000	35.216	1.71
$J_{1,t}^{1/2}$	0.216	0.265	6.72	119.71	0.000	5.934	36.64

	FTSE 100						
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,981		1,519	0.7668		1,562	0.7885
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	1.141	1.502	6.99	89.01	0.060	26.972	5,588.00
$RV_t^{1/2}$	0.951	0.486	1.90	11.13	0.246	5.193	10,819.00
J_t	0.091	0.196	8.08	108.22	0.000	3.519	468.45
$J_t^{1/2}$	0.217	0.210	1.74	9.22	0.000	1.876	370.24
$J_{1,t}$	0.101	0.200	6.30	61.82	0.000	2.725	360.08
$J_{1,t}^{1/2}$	0.233	0.216	1.60	7.94	0.000	1.651	349.39

	DJ Euro Stoxx 50						
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,901		1,545	0.8127		1,547	0.8138
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	1.839	2.931	8.60	140.52	0.125	65.443	5,585.50
$RV_t^{1/2}$	1.182	0.664	2.50	14.65	0.354	8.090	10,773.00
J_t	0.171	0.537	24.80	851.64	0.000	19.308	200.05
$J_t^{1/2}$	0.303	0.282	2.97	29.59	0.000	4.394	479.35
$J_{1,t}$	0.178	0.535	17.33	451.29	0.000	16.154	194.57
$J_{1,t}^{1/2}$	0.308	0.289	2.99	24.85	0.000	4.019	255.96

Notes: The Table show the mean, standard deviation, skewness, kurtosis, minimum and maximum summary statistics for realised variation (RV_t), jump variation (J_t, $J_{1,t}$) and their square root counterparts for the three equity index futures contracts. LB (10) denotes the Ljung Box test statistic for serial correlation up to 10 lags. The table also shows the number of observations (N(Days)) in each series and the number of days containing a jump ($N(J_t^+)$, $N(J_{1,t}^+)$). $J_{1,t}$ refers to jump series calculated using the one interval staggered measure of bipower variation.

Table 4.4.3.4. Summary Statistics for Daily Realised Volatility and Jump Series for Interest Rate Futures.

	US 10-Year T- Bond						
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,905		1,518	0.7969		1,545	0.8110
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	0.125	0.149	6.64	82.70	0.016	2.870	507.06
$RV_t^{1/2}$	0.324	0.142	2.36	13.43	0.125	1.694	1,670.00
J_t	0.019	0.048	8.54	102.42	0.000	0.857	3.68
$J_t^{1/2}$	0.099	0.094	2.52	15.20	0.000	0.926	34.89
$J_{1,t}$	0.022	0.063	10.69	159.02	0.000	1.239	6.52
$J_{1,t}^{1/2}$	0.106	0.104	2.90	19.43	0.000	1.113	26.00

	UK Gilt						
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	1,969		1,701	0.8639		1,746	0.8867
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	0.112	0.099	9.54	212.96	0.016	2.620	2,175.40
$RV_t^{1/2}$	0.317	0.109	1.96	14.82	0.126	1.619	4,524.70
J_t	0.014	0.023	5.74	56.92	0.000	0.338	116.44
$J_t^{1/2}$	0.097	0.071	1.33	7.31	0.000	0.581	174.81
$J_{1,t}$	0.018	0.034	14.33	367.70	0.000	1.010	61.16
$J_{1,t}^{1/2}$	0.109	0.078	1.92	14.85	0.000	1.005	189.23

	Euro Bund						
	N(Days)		$N(J_t^+)$	$Prop(J_t^+)$		$N(J_{1,t}^+)$	$Prop(J_{1,t}^+)$
	2,022		1,694	0.8378		1,700	0.8408
	MEAN	**STD DEV**	**SKEW**	**KURT**	**MIN**	**MAX**	**LB (10)**
RV_t	0.092	0.081	6.53	103.17	0.012	1.766	2,073.10
$RV_t^{1/2}$	0.287	0.101	1.81	11.28	0.109	1.329	3,882.10
J_t	0.010	0.015	5.54	53.08	0.000	0.240	32.06
$J_t^{1/2}$	0.078	0.059	1.23	6.77	0.000	0.489	38.94
$J_{1,t}$	0.011	0.021	7.98	106.82	0.000	0.417	11.76
$J_{1,t}^{1/2}$	0.083	0.066	1.68	10.04	0.000	0.646	38.39

Notes: The Table show the mean, standard deviation, skewness, kurtosis, minimum and maximum summary statistics for realised variation (RV_t), jump variation (J_t, $J_{1,t}$) and their square root counterparts for the three interest rate futures futures contracts. LB (10) denotes the Ljung Box test statistic for serial correlation up to 10 lags. The table also shows the number of observations (N(Days)) in each series and the number of days containing a jump ($N(J_t^+)$, $N(J_{1,t}^+)$). $J_{1,t}$ refers to jump series calculated using the one interval staggered measure of bipower variation.

Interestingly, adjustment for market microstructure noise by using the staggered measure of realised bipower variation finds more days containing jumps than when using the standard measure of bipower variation for all futures markets except the S&P 500 E-Mini, confirming earlier discussion that market microstructure frictions bias against finding jumps. In addition, this adjustment also results in jump variation contributing much more towards total return variation. This is also the case for the S&P 500 E-Mini futures market, which shows jumps making a slightly higher contribution to realised variation after adjusting for market microstructure effects even though there are fewer days identified as containing jumps. This may suggest that, in addition to identifying days containing jumps more accurately, the one-period staggered version of the test also measures the extent of the jump variation more precisely.

Turning to the distributional properties of the series, as shown by Table 4.4.3.3, the equity futures markets are most volatile, followed by the foreign exchange market. Despite being the most volatile markets by far, the equity index futures show the lowest proportions of days containing jumps and the lowest contributions of jump variation to total variation (ranging from 0.080 to 0.097) indicating that continuous sample path variation is the source of the high realised variation. Despite being the least volatile class of markets, the data in Table 4.4.3.4 shows that the bond futures markets have the highest proportion of days containing jumps with those jumps identified making the largest contribution to total variation of all three asset classes (up to 0.176 for the US 10-Year T-Bond when using staggered bipower variation). For each market, realised variation and jump variation series show large skewness and kurtosis statistics showing long right hand tails and leptokurtic properties, emphasising the magnitude of variation caused by jumps. Both statistics for jump variation are larger after adjusting for market microstructure noise indicating that annihilating these frictions detects larger jumps. Maximum values compared to the mean reveal some extremely volatile days for each market and for each of the equity index futures markets in particular. Ljung-Box statistics show a very strong degree of own serial correlation in realised variation which, although still statistically significant, is much lower for jump variation, and is reduced substantially in most cases by implementing staggered bipower variation. This suggests that remarkably less own dynamic dependence exists in the component of realised variation caused by the discontinuous sample path price process as compared to the serial correlation in the continuous sample path price movements, which confirms the recent finding of Andersen, Bollerslev and Diebold (2007b). In further support of their results, the square root adjustment of each series brings it closer to a Gaussian distribution, but increases the degree of autocorrelation.

The most important points to note from this preliminary analysis are as follows. First, jumps are found to be prevalent in this sample of futures markets, although this crude test may incorrectly identify continuous sample path price movements as jumps. Second, jump variation is not the dominant driver of quadratic variation, but contributes an important portion of realised variation nonetheless. Third, serial dependence in realised variation is caused mainly by the continuous sample path variation. Fourth, adjustment for market microstructure noise influences causes dramatic changes to the measurement of jumps as shown by: the substantial changes to the distributional and time series properties of the jump series; the identification of more days containing jumps; and a larger contribution to quadratic variation from the discontinuous sample path price process. Motivated by these findings, the following section adopts asymptotic theory to isolate statistically significant jumps, and in so doing assesses the empirical performance of the alternative tests described in section 4.3.3 for a range of significance levels.

4.4.4 Significant Daily Jumps

Tables 4.4.4.1 to 4.4.4.9 show brief summary statistics for the jump series measured by equations (4.30a), (4.30b) and (4.30c), which calculate significant jumps according to the alternative ratios W_t, Z_t and U_t specified in equations (4.27), (4.28) and (4.29). These tables therefore allow the comparison of descriptive statistics (mean, standard deviation and Ljung Box serial correlation test statistics up to ten lags) across the alternative jump measures and across a range of statistical significance levels. Given the importance of market microstructure noise identified in previous sections and in the extant literature, Tables 4.4.4.1 to 4.4.4.9 calculate significant jumps using the one period staggered version of realised bipower variation ($BV_{1,t}$) and tripower quarticity ($TQ_{1,t}$) as defined by equations (4.33) and (4.34) respectively, with the corresponding test statistics denoted by $W_{1,t}$, $Z_{1,t}$ and $U_{1,t}$.

Table 4.4.4.1. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for EUR-USD Futures.

$W_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$
1,819	722	361	357	514	247	264	323	155	166	239	117	121
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.025	0.070	6.32	0.021	0.070	5.13	0.016	0.069	4.83	0.014	0.067	1.92
J_t^+	0.063	0.099	1.43	0.074	0.115	0.45	0.093	0.140	0.14	0.106	0.158	0.11
$J_t^{1/2}$	0.089	0.130	10.91	0.069	0.127	6.59	0.049	0.119	6.10	0.038	0.112	2.31
$(J_t^{1/2})^+$	0.225	0.109	9.48	0.244	0.120	3.41	0.274	0.134	0.67	0.291	0.145	0.18
J_t/RV_t	0.096	0.133	12.39	0.078	0.134	9.49	0.057	0.128	7.08	0.046	0.122	6.56
$(J_t/RV_t)^+$	0.243	0.096	4.34	0.276	0.094	2.10	0.321	0.091	3.86	0.347	0.091	1.88
JD	2.519	1.925	17.97	3.538	3.044	20.21	5.637	5.365	16.32	7.588	7.828	12.06
$JA>0$	0.226	0.110	3.70	0.247	0.122	1.45	0.281	0.137	0.99	0.298	0.147	0.35
$JA<0$	-0.225	0.109	1.56	-0.241	0.118	1.32	-0.268	0.131	0.28	-0.286	0.144	0.15

$Z_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$
1,819	689	338	347	419	202	214	222	112	110	120	58	62
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.025	0.070	5.88	0.019	0.069	5.12	0.014	0.068	2.62	0.010	0.065	2.33
J_t^+	0.065	0.101	1.25	0.082	0.125	0.33	0.113	0.164	0.31	0.146	0.209	0.11
$J_t^{1/2}$	0.087	0.130	12.12	0.060	0.124	9.55	0.037	0.111	3.05	0.022	0.096	4.70
$(J_t^{1/2})^+$	0.230	0.110	8.04	0.258	0.124	2.34	0.301	0.149	1.10	0.340	0.176	0.27
J_t/RV_t	0.094	0.134	16.04	0.069	0.133	13.22	0.044	0.121	11.15	0.027	0.105	11.11
$(J_t/RV_t)^+$	0.249	0.094	3.15	0.299	0.090	4.13	0.358	0.087	1.39	0.413	0.085	0.85
JD	2.640	2.126	18.24	4.342	3.796	23.15	8.213	8.856	10.02	15.176	17.278	29.38
$JA>0$	0.231	0.111	3.47	0.264	0.127	1.60	0.307	0.151	0.51	0.348	0.174	0.11
$JA<0$	-0.229	0.110	2.01	-0.254	0.122	0.57	-0.296	0.148	0.04	-0.332	0.179	0.05

$U_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$
1,819	684	342	342	439	212	227	251	125	126	164	80	84
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.024	0.070	6.33	0.019	0.069	4.40	0.014	0.068	1.90	0.011	0.065	2.43
J_t^+	0.065	0.102	1.31	0.080	0.123	0.29	0.104	0.155	0.13	0.121	0.184	0.15
$J_t^{1/2}$	0.086	0.130	9.62	0.061	0.124	4.40	0.040	0.113	1.96	0.028	0.101	5.95
$(J_t^{1/2})^+$	0.229	0.111	8.11	0.253	0.125	2.17	0.289	0.142	0.20	0.309	0.162	0.31
J_t/RV_t	0.093	0.134	12.93	0.070	0.132	6.88	0.047	0.123	4.99	0.034	0.111	9.65
$(J_t/RV_t)^+$	0.249	0.096	4.19	0.290	0.095	1.82	0.342	0.092	2.13	0.375	0.095	1.20
JD	2.659	2.152	13.20	4.144	3.544	9.04	7.224	6.879	13.88	11.025	12.047	6.83
$JA>0$	0.228	0.111	2.92	0.256	0.127	1.24	0.294	0.143	0.32	0.319	0.160	0.31
$JA<0$	-0.229	0.110	1.41	-0.250	0.123	0.89	-0.284	0.142	0.15	-0.300	0.163	0.18

Table 4.4.4.2. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for GBP-USD Futures.

$W_{1,t}$												
α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,938	957	511	441	720	380	335	507	271	232	392	210	179
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.019	0.031	46.84	0.016	0.032	43.22	0.013	0.031	35.15	0.011	0.030	36.79
J_t^+	0.039	0.035	15.58	0.044	0.038	7.59	0.051	0.043	3.72	0.055	0.047	2.19
$J_t^{1/2}$	0.092	0.104	140.02	0.074	0.104	124.05	0.056	0.101	100.41	0.045	0.095	106.82
$(J_t^{1/2})^+$	0.186	0.066	35.68	0.198	0.068	16.03	0.214	0.071	7.47	0.222	0.073	3.88
J_t/RV_t	0.128	0.148	340.70	0.108	0.153	269.59	0.086	0.152	210.84	0.071	0.147	189.05
$(J_t/RV_t)^+$	0.259	0.102	39.01	0.291	0.096	14.85	0.328	0.091	6.36	0.353	0.087	2.83
JD	2.020	1.636	89.93	2.684	2.457	134.81	3.814	3.998	137.77	4.936	5.681	128.05
$JA>0$	0.187	0.066	7.02	0.200	0.069	4.35	0.214	0.072	2.30	0.223	0.075	1.76
$JA<0$	-0.184	0.065	7.37	-0.197	0.067	4.44	-0.214	0.070	2.17	-0.223	0.071	1.01

$Z_{1,t}$												
α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,938	907	478	423	615	320	291	364	195	168	228	121	106
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.019	0.032	50.51	0.015	0.032	46.10	0.011	0.030	34.06	0.008	0.029	16.76
J_t^+	0.040	0.036	10.66	0.047	0.040	5.87	0.057	0.048	1.67	0.066	0.056	0.76
$J_t^{1/2}$	0.089	0.105	176.70	0.065	0.104	153.17	0.043	0.094	121.56	0.029	0.083	80.96
$(J_t^{1/2})^+$	0.190	0.066	20.96	0.206	0.069	12.43	0.226	0.074	3.34	0.244	0.081	1.21
J_t/RV_t	0.125	0.149	393.99	0.099	0.153	307.91	0.068	0.147	226.83	0.048	0.133	151.29
$(J_t/RV_t)^+$	0.266	0.099	20.27	0.310	0.091	10.49	0.364	0.082	1.70	0.404	0.079	2.28
JD	2.131	1.786	156.56	3.143	3.309	168.34	5.298	6.653	97.95	8.471	11.438	65.23
$JA>0$	0.192	0.067	6.50	0.209	0.070	3.89	0.227	0.077	1.78	0.243	0.083	1.06
$JA<0$	-0.188	0.065	5.43	-0.204	0.067	3.43	-0.226	0.072	0.67	-0.246	0.078	0.18

$U_{1,t}$												
α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,938	902	486	416	629	335	294	403	215	188	293	159	134
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.018	0.031	49.21	0.015	0.032	37.68	0.011	0.030	35.68	0.009	0.029	22.88
J_t^+	0.040	0.036	13.71	0.047	0.040	5.35	0.054	0.046	2.53	0.060	0.052	0.96
$J_t^{1/2}$	0.087	0.104	166.67	0.066	0.104	109.92	0.046	0.096	102.49	0.035	0.088	59.06
$(J_t^{1/2})^+$	0.188	0.066	30.61	0.205	0.069	13.03	0.221	0.073	4.92	0.232	0.078	1.51
J_t/RV_t	0.124	0.149	355.43	0.099	0.153	236.04	0.073	0.147	181.58	0.057	0.139	105.45
$(J_t/RV_t)^+$	0.265	0.101	27.75	0.305	0.094	12.65	0.350	0.088	3.27	0.375	0.086	1.89
JD	2.143	1.802	129.25	3.073	3.067	99.69	4.801	5.465	117.12	6.582	7.718	59.61
$JA>0$	0.189	0.066	6.96	0.206	0.069	3.39	0.221	0.075	1.78	0.233	0.080	1.08
$JA<0$	-0.186	0.066	6.17	-0.203	0.068	4.49	-0.221	0.071	1.36	-0.231	0.075	0.49

Table 4.4.4.3. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for JPY-USD Futures.

						$W_{1,t}$						
α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,939	793	406	377	563	297	259	372	193	176	287	149	135
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.023	0.069	63.15	0.019	0.061	10.30	0.015	0.060	8.60	0.013	0.052	7.67
J_t^+	0.056	0.098	43.70	0.065	0.099	1.65	0.081	0.118	1.17	0.085	0.110	1.38
$J_t^{1/2}$	0.086	0.126	21.75	0.066	0.121	22.94	0.049	0.115	19.31	0.039	0.105	14.37
$(J_t^{1/2})^+$	0.209	0.113	27.67	0.228	0.116	3.42	0.253	0.129	2.07	0.261	0.129	2.11
J_t/RV_t	0.098	0.132	20.03	0.079	0.133	20.18	0.059	0.128	15.10	0.049	0.122	17.30
$(J_t/RV_t)^+$	0.240	0.092	8.30	0.273	0.088	4.59	0.309	0.087	2.80	0.330	0.087	1.76
JD	2.441	1.896	7.23	3.429	2.988	14.65	5.194	4.942	7.76	6.738	6.741	10.48
$JA>0$	0.218	0.114	5.09	0.236	0.123	1.68	0.265	0.138	1.56	0.270	0.131	0.81
$JA<0$	-0.201	0.111	2.60	-0.219	0.107	0.25	-0.240	0.118	0.25	-0.252	0.128	0.23

						$Z_{1,t}$						
α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,939	753	387	355	452	239	208	234	123	109	117	63	52
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.022	0.062	12.14	0.018	0.061	11.52	0.012	0.059	5.13	0.008	0.049	8.19
J_t^+	0.057	0.088	6.10	0.075	0.109	1.82	0.100	0.142	0.47	0.130	0.153	0.33
$J_t^{1/2}$	0.082	0.123	21.59	0.057	0.120	19.53	0.034	0.105	8.88	0.019	0.086	10.85
$(J_t^{1/2})^+$	0.212	0.108	17.16	0.246	0.123	3.42	0.281	0.147	1.34	0.322	0.162	0.68
J_t/RV_t	0.096	0.132	21.64	0.069	0.131	13.93	0.042	0.118	9.35	0.025	0.099	14.10
$(J_t/RV_t)^+$	0.246	0.089	5.61	0.295	0.084	5.95	0.350	0.085	1.49	0.407	0.088	0.46
JD	2.563	2.121	15.10	4.273	3.955	4.17	8.146	7.767	14.47	16.207	18.402	7.57
$JA>0$	0.222	0.115	5.19	0.256	0.130	2.17	0.291	0.157	0.52	0.331	0.165	0.39
$JA<0$	-0.203	0.100	1.08	-0.236	0.114	0.20	-0.270	0.135	0.26	-0.315	0.163	0.14

						$U_{1,t}$						
α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,939	727	382	345	477	257	220	298	157	141	183	104	79
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.022	0.061	13.01	0.017	0.061	11.00	0.013	0.052	6.83	0.010	0.050	7.12
J_t^+	0.057	0.090	3.80	0.071	0.106	1.36	0.083	0.108	1.56	0.103	0.131	0.88
$J_t^{1/2}$	0.080	0.123	26.39	0.058	0.119	21.49	0.040	0.106	10.97	0.027	0.095	11.98
$(J_t^{1/2})^+$	0.213	0.109	10.48	0.238	0.121	2.58	0.258	0.128	2.40	0.286	0.146	1.33
J_t/RV_t	0.093	0.132	21.57	0.071	0.131	15.32	0.050	0.123	12.66	0.034	0.109	15.69
$(J_t/RV_t)^+$	0.248	0.091	8.46	0.288	0.088	3.91	0.327	0.087	1.83	0.360	0.093	1.30
JD	2.654	2.273	15.60	4.048	3.663	11.50	6.488	6.560	13.04	10.429	10.828	8.26
$JA>0$	0.221	0.116	3.40	0.246	0.128	1.41	0.266	0.129	0.87	0.288	0.146	0.66
$JA<0$	-0.204	0.101	0.73	-0.228	0.112	0.20	-0.249	0.127	0.35	-0.285	0.146	0.33

Table 4.4.4.4. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for S&P 500 E-Mini Futures.

					$W_{1,t}$							
α		0.05			0.01			0.001			0.0001	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,993	574	310	257	352	184	162	218	111	104	135	74	58
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.089	0.837	0.79	0.072	0.836	0.19	0.061	0.834	0.17	0.052	0.833	0.14
J_t^+	0.308	1.540	0.20	0.410	1.956	0.03	0.559	2.472	0.02	0.764	3.125	0.01
$J_t^{1/2}$	0.124	0.271	9.72	0.085	0.255	5.58	0.060	0.240	2.65	0.042	0.224	2.98
$(J_t^{1/2})^+$	0.431	0.350	26.82	0.484	0.420	4.53	0.551	0.506	1.34	0.622	0.616	0.32
J_t/RV_t	0.059	0.104	25.21	0.043	0.100	19.04	0.030	0.092	18.81	0.021	0.083	11.82
$(J_t/RV_t)^+$	0.206	0.084	4.94	0.245	0.086	0.44	0.279	0.092	0.14	0.315	0.100	0.61
JD	3.471	3.407	31.37	5.610	5.595	47.36	9.074	9.588	19.14	14.694	16.031	11.07
$JA>0$	0.424	0.411	2.56	0.481	0.514	0.26	0.567	0.636	0.06	0.646	0.757	0.04
$JA<0$	-0.445	0.262	6.52	-0.497	0.288	2.24	-0.544	0.323	0.82	-0.612	0.387	0.27

					$Z_{1,t}$							
α		0.05			0.01			0.001			0.0001	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,993	533	291	235	294	148	142	120	60	57	56	29	27
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.087	0.837	0.49	0.069	0.836	0.19	0.052	0.833	0.15	0.042	0.831	0.09
J_t^+	0.324	1.596	0.20	0.466	2.136	0.03	0.856	3.305	0.01	1.507	4.768	0.00
$J_t^{1/2}$	0.118	0.270	7.76	0.076	0.251	4.43	0.040	0.223	2.55	0.025	0.204	2.20
$(J_t^{1/2})^+$	0.442	0.360	22.40	0.514	0.451	2.85	0.669	0.642	0.25	0.877	0.866	0.06
J_t/RV_t	0.057	0.104	26.03	0.038	0.098	24.23	0.020	0.082	9.47	0.011	0.068	4.39
$(J_t/RV_t)^+$	0.213	0.083	3.16	0.260	0.086	0.55	0.327	0.101	0.10	0.394	0.114	0.10
JD	3.739	3.781	33.28	6.788	6.804	56.65	15.941	18.767	12.50	34.091	41.007	6.71
$JA>0$	0.431	0.423	2.01	0.521	0.562	0.17	0.719	0.823	0.02	0.968	1.125	0.01
$JA<0$	-0.461	0.267	5.34	-0.514	0.300	1.87	-0.638	0.384	0.29	-0.780	0.453	0.10

					$U_{1,t}$							
α		0.05			0.01			0.001			0.0001	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,993	537	294	243	310	164	146	158	87	71	82	45	37
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.086	0.837	0.79	0.069	0.835	0.18	0.053	0.829	0.13	0.044	0.826	0.09
J_t^+	0.321	1.591	0.16	0.446	2.081	0.02	0.672	2.880	0.01	1.063	3.962	0.00
$J_t^{1/2}$	0.118	0.269	9.57	0.078	0.252	2.94	0.047	0.226	3.66	0.030	0.207	2.04
$(J_t^{1/2})^+$	0.438	0.359	21.58	0.501	0.442	2.84	0.595	0.566	0.56	0.727	0.735	0.06
J_t/RV_t	0.057	0.103	25.00	0.039	0.098	18.08	0.024	0.086	13.11	0.015	0.074	5.13
$(J_t/RV_t)^+$	0.211	0.084	4.33	0.253	0.087	0.45	0.301	0.098	0.36	0.354	0.111	0.16
JD	3.711	3.659	28.97	6.372	6.548	40.61	12.541	13.795	13.01	23.420	26.432	28.95
$JA>0$	0.427	0.422	20.69	0.496	0.541	0.22	0.588	0.690	0.04	0.755	0.920	0.01
$JA<0$	-0.451	0.265	5.59	-0.507	0.295	1.54	-0.603	0.366	0.41	-0.693	0.424	0.17

Table 4.4.4.5. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for FTSE 100 Futures.

			$W_{1,t}$									
α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$
1,981	687	340	344	450	228	221	285	151	134	187	100	87
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.072	0.196	78.28	0.056	0.183	21.00	0.041	0.173	11.04	0.031	0.163	8.53
J_t^+	0.208	0.288	87.96	0.245	0.319	22.70	0.287	0.372	5.75	0.331	0.429	1.36
$J_t^{1/2}$	0.138	0.231	31.08	0.098	0.214	17.64	0.067	0.192	11.80	0.047	0.170	11.89
$(J_t^{1/2})^+$	0.398	0.224	241.39	0.433	0.239	71.72	0.467	0.262	17.49	0.500	0.285	4.38
J_t/RV_t	0.069	0.104	24.32	0.053	0.103	19.22	0.038	0.096	11.19	0.028	0.088	10.98
$(J_t/RV_t)^+$	0.199	0.075	5.99	0.231	0.073	3.41	0.262	0.075	2.55	0.291	0.076	1.42
JD	2.879	2.455	17.67	4.399	4.102	10.46	6.954	6.450	23.46	10.618	10.351	12.51
$JA>0$	0.397	0.231	35.91	0.436	0.244	9.01	0.464	0.262	2.30	0.506	0.279	0.61
$JA<0$	-0.399	0.217	32.40	-0.431	0.236	9.58	-0.471	0.263	3.05	-0.494	0.293	0.95

			$Z_{1,t}$									
α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$.	$N(JA<0)$
1,981	658	328	327	380	192	188	183	96	87	93	48	45
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.072	0.196	79.74	0.050	0.180	10.77	0.032	0.166	6.41	0.021	0.151	7.68
J_t^+	0.215	0.292	77.66	0.262	0.337	11.03	0.351	0.434	0.99	0.452	0.542	0.26
$J_t^{1/2}$	0.135	0.231	32.06	0.086	0.207	8.15	0.048	0.174	7.93	0.028	0.143	14.44
$(J_t^{1/2})^+$	0.406	0.225	213.92	0.449	0.246	35.94	0.519	0.287	3.80	0.588	0.329	0.92
J_t/RV_t	0.067	0.105	22.02	0.047	0.102	9.06	0.027	0.089	13.36	0.016	0.075	21.20
$(J_t/RV_t)^+$	0.203	0.074	5.78	0.245	0.072	3.14	0.297	0.072	1.18	0.346	0.072	0.83
JD	3.006	2.661	12.83	5.211	5.012	8.12	10.791	10.473	11.26	21.130	24.730	12.71
$JA>0$	0.405	0.232	31.64	0.447	0.250	4.06	0.508	0.284	0.40	0.598	0.314	0.14
$JA<0$	-0.408	0.218	30.51	-0.450	0.242	5.77	-0.531	0.292	1.08	-0.576	0.347	0.28

			$U_{1,t}$									
α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$	$N(J^+)$	$N(JA>0)$	$N(JA<0)$
1,981	641	321	320	395	202	193	209	112	97	120	64	56
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.068	0.187	35.99	0.051	0.181	16.07	0.033	0.165	13.39	0.024	0.153	8.13
J_t^+	0.209	0.281	61.67	0.258	0.333	15.33	0.316	0.411	2.04	0.397	0.491	0.32
$J_t^{1/2}$	0.129	0.226	17.57	0.089	0.209	15.22	0.052	0.175	17.97	0.033	0.151	13.56
$(J_t^{1/2})^+$	0.400	0.222	191.38	0.445	0.245	46.69	0.489	0.277	6.21	0.549	0.310	1.20
J_t/RV_t	0.066	0.105	22.67	0.048	0.101	14.79	0.030	0.090	13.02	0.020	0.079	15.22
$(J_t/RV_t)^+$	0.204	0.075	5.30	0.240	0.074	3.43	0.282	0.076	1.88	0.323	0.077	0.62
JD	3.086	2.730	22.91	5.013	4.850	8.14	9.495	9.511	15.39	16.336	15.635	22.14
$JA>0$	0.400	0.224	23.61	0.444	0.250	6.58	0.490	0.272	0.93	0.557	0.295	0.17
$JA<0$	-0.399	0.220	28.20	-0.446	0.240	5.75	-0.488	0.285	1.04	-0.540	0.328	0.33

Table 4.4.4.6. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for DJ Euro Stoxx 50 Futures.

$W_{1,t}$

α		0.05			0.01			0.001			0.0001	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,901	777	388	382	531	260	265	341	173	164	238	125	109
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.137	0.535	82.51	0.107	0.519	42.38	0.072	0.335	47.93	0.057	0.300	44.48
J_t^+	0.335	0.797	71.04	0.384	0.927	22.18	0.400	0.705	17.74	0.452	0.738	9.26
$J_t^{1/2}$	0.197	0.313	30.64	0.144	0.294	18.20	0.096	0.250	12.14	0.071	0.227	14.70
$(J_t^{1/2})^+$	0.483	0.320	287.37	0.514	0.346	84.55	0.537	0.334	27.03	0.570	0.357	12.83
J_t/RV_t	0.084	0.113	75.29	0.066	0.114	48.61	0.049	0.109	44.48	0.037	0.102	13.14
$(J_t/RV_t)^+$	0.206	0.078	6.72	0.237	0.076	5.06	0.271	0.073	11.57	0.297	0.072	0.91
JD	2.447	2.330	92.36	3.583	3.792	51.40	5.579	6.167	71.40	8.004	8.618	71.40
$JA>0$	0.461	0.293	41.94	0.490	0.312	13.11	0.527	0.351	6.12	0.560	0.394	4.73
$JA<0$	-0.509	0.345	36.57	-0.543	0.376	14.11	-0.553	0.318	2.70	-0.591	0.312	2.43

$Z_{1,t}$

α		0.05			0.01			0.001			0.0001	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,901	770	378	385	477	238	233	260	137	119	143	79	61
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.135	0.534	75.32	0.102	0.524	46.87	0.070	0.487	36.41	0.045	0.306	47.80
J_t^+	0.333	0.799	67.99	0.405	0.986	21.71	0.509	1.232	6.79	0.601	0.957	4.40
$J_t^{1/2}$	0.195	0.311	30.35	0.131	0.291	15.94	0.079	0.252	15.09	0.048	0.207	28.31
$(J_t^{1/2})^+$	0.480	0.319	269.65	0.523	0.364	75.65	0.574	0.424	21.16	0.644	0.433	5.38
J_t/RV_t	0.084	0.113	82.00	0.062	0.113	55.97	0.040	0.104	23.01	0.025	0.090	9.78
$(J_t/RV_t)^+$	0.208	0.078	8.35	0.247	0.074	3.29	0.293	0.071	2.09	0.332	0.072	0.61
JD	2.469	2.456	87.16	3.985	4.648	66.19	7.239	9.022	64.41	13.049	16.369	19.20
$JA>0$	0.460	0.294	37.13	0.498	0.333	15.77	0.536	0.389	5.33	0.611	0.459	2.06
$JA<0$	-0.504	0.343	37.16	-0.555	0.393	12.70	-0.627	0.462	6.54	-0.703	0.399	2.21

$U_{1,t}$

α		0.05			0.01			0.001			0.0001	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,901	729	369	360	466	237	229	269	148	121	167	98	69
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.132	0.534	79.46	0.091	0.362	45.30	0.060	0.302	49.75	0.046	0.293	50.67
J_t^+	0.344	0.819	62.80	0.371	0.658	30.84	0.425	0.701	11.66	0.529	0.852	5.97
$J_t^{1/2}$	0.188	0.311	31.39	0.127	0.274	15.47	0.078	0.232	16.93	0.053	0.209	23.48
$(J_t^{1/2})^+$	0.489	0.324	243.68	0.518	0.322	67.54	0.554	0.345	18.19	0.609	0.399	6.87
J_t/RV_t	0.081	0.114	73.16	0.061	0.113	48.33	0.041	0.104	15.11	0.028	0.092	15.66
$(J_t/RV_t)^+$	0.212	0.078	6.46	0.247	0.075	5.11	0.287	0.073	0.98	0.317	0.074	0.87
JD	2.609	2.536	87.45	4.080	4.659	67.92	7.078	7.572	84.08	11.211	12.963	32.55
$JA>0$	0.466	0.297	37.01	0.496	0.323	10.78	0.538	0.374	5.70	0.570	0.426	2.93
$JA<0$	-0.513	0.349	32.36	-0.540	0.320	8.66	-0.573	0.306	2.68	-0.664	0.351	1.45

Table 4.4.4.7. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for US 10-Year Treasury Bond Futures.

$W_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)
1,905	871	399	440	653	310	323	453	219	221	358	171	177
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.019	0.063	6.13	0.017	0.064	7.16	0.015	0.063	8.01	0.013	0.061	9.27
J_t^+	0.042	0.089	4.18	0.050	0.101	3.11	0.061	0.117	1.61	0.068	0.128	0.99
$J_t^{1/2}$	0.078	0.114	19.38	0.064	0.114	19.31	0.049	0.110	19.68	0.041	0.105	14.80
$(J_t^{1/2})^+$	0.170	0.113	17.68	0.187	0.123	11.93	0.207	0.136	5.59	0.218	0.143	3.54
J_t/RV_t	0.125	0.160	177.85	0.106	0.163	129.33	0.085	0.162	102.59	0.072	0.158	79.06
$(J_t/RV_t)^+$	0.273	0.123	10.27	0.311	0.120	3.86	0.356	0.116	1.73	0.385	0.114	1.74
JD	2.189	1.928	184.20	2.919	2.973	104.09	4.210	4.818	62.51	5.331	6.255	62.13
$JA>0$	0.172	0.112	0.93	0.186	0.120	1.12	0.206	0.134	0.92	0.218	0.139	0.51
$JA<0$	-0.172	0.117	10.19	-0.192	0.128	6.47	-0.212	0.139	3.58	-0.223	0.149	2.53

$Z_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)
1,905	838	390	419	563	272	271	354	165	180	228	101	122
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.019	0.064	5.71	0.017	0.064	6.73	0.013	0.063	7.86	0.011	0.061	7.69
J_t^+	0.043	0.090	4.10	0.056	0.107	2.33	0.073	0.130	0.88	0.088	0.155	0.34
$J_t^{1/2}$	0.076	0.115	17.86	0.059	0.114	21.08	0.042	0.108	18.22	0.030	0.098	12.48
$(J_t^{1/2})^+$	0.174	0.114	17.48	0.198	0.128	9.20	0.227	0.146	3.98	0.248	0.164	1.33
J_t/RV_t	0.123	0.160	191.80	0.098	0.164	127.02	0.072	0.159	84.66	0.053	0.148	60.05
$(J_t/RV_t)^+$	0.279	0.122	5.89	0.332	0.116	4.60	0.390	0.110	1.03	0.443	0.104	1.40
JD	2.275	2.064	179.38	3.386	3.722	88.46	5.391	6.519	45.74	8.374	11.074	55.25
$JA>0$	0.176	0.112	0.71	0.197	0.124	0.75	0.232	0.144	0.44	0.254	0.163	0.52
$JA<0$	-0.176	0.118	10.34	-0.206	0.135	4.10	-0.227	0.149	2.60	-0.248	0.167	1.89

$U_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)	$N(J^+)$	N(JA>0)	N(JA<0)
1,905	819	405	414	562	290	272	373	189	184	273	133	140
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.019	0.063	5.95	0.016	0.063	7.53	0.013	0.061	8.04	0.011	0.061	7.26
J_t^+	0.043	0.091	4.26	0.055	0.107	2.41	0.066	0.125	0.89	0.077	0.143	0.50
$J_t^{1/2}$	0.074	0.114	16.61	0.058	0.113	14.16	0.042	0.105	14.71	0.033	0.100	11.41
$(J_t^{1/2})^+$	0.173	0.115	16.47	0.196	0.129	8.45	0.214	0.141	3.29	0.230	0.155	1.56
J_t/RV_t	0.121	0.161	158.30	0.097	0.163	80.71	0.074	0.159	81.89	0.059	0.151	52.76
$(J_t/RV_t)^+$	0.281	0.123	8.39	0.329	0.119	5.16	0.378	0.116	1.74	0.412	0.115	1.33
JD	2.328	2.148	136.44	3.392	3.404	64.39	5.116	5.848	66.14	6.982	8.132	56.96
$JA>0$	0.171	0.111	1.90	0.187	0.123	1.72	0.209	0.135	1.04	0.228	0.149	0.21
$JA<0$	-0.175	0.119	8.95	-0.205	0.134	4.97	-0.219	0.146	2.79	-0.233	0.161	2.48

Table 4.4.4.8. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for UK Gilt Futures.

$W_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,969	1072	497	566	820	383	432	578	288	286	416	203	211
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.015	0.035	30.24	0.014	0.035	26.63	0.011	0.035	12.47	0.009	0.035	8.33
J_t^+	0.028	0.043	28.21	0.033	0.049	16.29	0.039	0.056	3.97	0.044	0.064	1.51
$J_t^{1/2}$	0.082	0.093	40.78	0.068	0.095	37.01	0.052	0.093	18.53	0.040	0.088	21.13
$(J_t^{1/2})^+$	0.151	0.074	155.26	0.163	0.078	89.48	0.177	0.085	22.08	0.189	0.093	7.61
J_t/RV_t	0.124	0.134	40.83	0.106	0.139	36.24	0.084	0.140	17.03	0.066	0.135	27.74
$(J_t/RV_t)^+$	0.227	0.096	8.49	0.255	0.093	7.62	0.287	0.093	6.22	0.314	0.094	3.01
JD	1.837	1.298	12.30	2.402	1.877	15.54	3.409	2.751	15.09	4.680	4.346	11.04
$JA>0$	0.152	0.070	15.34	0.164	0.073	9.56	0.176	0.076	4.32	0.189	0.082	1.47
$JA<0$	-0.152	0.077	24.71	-0.163	0.084	13.81	-0.179	0.093	1.97	-0.190	0.102	1.24

$Z_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,969	1068	498	563	753	355	393	462	235	225	268	136	131
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.015	0.035	30.31	0.013	0.035	23.78	0.010	0.035	9.10	0.008	0.034	6.53
J_t^+	0.028	0.043	30.29	0.034	0.050	11.77	0.043	0.062	2.20	0.056	0.076	0.74
$J_t^{1/2}$	0.082	0.093	41.40	0.064	0.095	34.72	0.044	0.090	19.04	0.029	0.083	17.54
$(J_t^{1/2})^+$	0.152	0.074	170.31	0.168	0.079	62.47	0.186	0.090	11.49	0.215	0.102	3.25
J_t/RV_t	0.124	0.134	41.42	0.101	0.140	31.40	0.073	0.138	30.76	0.049	0.128	28.08
$(J_t/RV_t)^+$	0.228	0.095	9.06	0.264	0.091	6.47	0.309	0.091	2.66	0.359	0.091	1.30
JD	1.843	1.306	8.61	2.616	2.069	9.94	4.262	3.860	18.42	7.146	7.373	18.91
$JA>0$	0.152	0.070	18.87	0.169	0.073	7.99	0.183	0.080	2.73	0.211	0.090	0.88
$JA<0$	-0.152	0.077	25.29	-0.168	0.085	9.10	-0.190	0.100	1.14	-0.218	0.114	0.44

$U_{1,t}$

α	0.05			0.01			0.001			0.0001		
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
1,969	1030	486	544	739	355	384	474	238	236	305	152	153
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.015	0.035	29.33	0.013	0.035	22.67	0.010	0.035	8.21	0.008	0.034	7.10
J_t^+	0.029	0.044	26.22	0.034	0.051	11.04	0.041	0.061	1.98	0.050	0.072	1.02
$J_t^{1/2}$	0.080	0.094	39.72	0.062	0.094	25.42	0.044	0.089	18.28	0.031	0.083	20.70
$(J_t^{1/2})^+$	0.153	0.074	143.50	0.166	0.080	59.87	0.182	0.089	10.09	0.201	0.100	4.51
J_t/RV_t	0.121	0.135	39.19	0.099	0.140	23.05	0.073	0.137	22.00	0.053	0.129	26.27
$(J_t/RV_t)^+$	0.232	0.095	9.68	0.264	0.094	6.94	0.302	0.095	4.54	0.341	0.096	1.05
JD	1.912	1.364	8.52	2.665	2.033	10.95	4.152	3.642	5.55	6.382	6.253	9.44
$JA>0$	0.153	0.070	15.26	0.166	0.074	8.65	0.180	0.079	2.10	0.199	0.088	0.98
$JA<0$	-0.153	0.078	22.52	-0.167	0.086	8.48	-0.185	0.098	1.24	-0.203	0.110	0.85

Table 4.4.4.9. Summary Statistics for Daily Jump Series Using $BV_{1,t}$ and $TQ_{1,t}$ for Euro Bund Futures.

$W_{1,t}$												
α		**0.05**			**0.01**			**0.001**			**0.0001**	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
2,022	884	400	473	645	292	345	432	193	233	313	134	173
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.009	0.022	6.94	0.008	0.022	6.78	0.006	0.021	5.35	0.005	0.020	6.11
J_t^+	0.021	0.029	6.84	0.024	0.033	4.05	0.029	0.037	1.20	0.033	0.042	0.73
$J_t^{1/2}$	0.057	0.077	14.22	0.045	0.076	20.33	0.033	0.071	16.33	0.025	0.067	17.06
$\left(J_t^{1/2}\right)^+$	0.129	0.064	35.46	0.140	0.069	14.98	0.152	0.074	3.48	0.165	0.080	1.79
J_t/RV_t	0.091	0.120	54.71	0.076	0.122	55.37	0.058	0.119	39.71	0.047	0.115	34.41
$(J_t/RV_t)^+$	0.209	0.092	5.83	0.238	0.090	3.13	0.273	0.091	1.29	0.301	0.092	0.62
JD	2.287	1.889	37.80	3.135	3.460	8.11	4.677	5.295	15.99	6.462	7.595	7.38
$JA>0$	0.126	0.062	8.30	0.138	0.066	5.18	0.147	0.070	1.70	0.160	0.076	0.55
$JA<0$	-0.133	0.066	6.07	-0.143	0.071	2.81	-0.158	0.078	1.00	-0.170	0.083	1.14

$Z_{1,t}$												
α		**0.05**			**0.01**			**0.001**			**0.0001**	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
2,022	894	410	474	594	263	322	345	152	189	216	97	115
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.009	0.022	6.83	0.007	0.022	5.35	0.006	0.021	6.08	0.004	0.020	7.34
J_t^+	0.021	0.029	6.42	0.025	0.034	3.11	0.033	0.041	1.12	0.041	0.048	0.73
$J_t^{1/2}$	0.057	0.077	13.85	0.042	0.076	16.06	0.028	0.070	17.70	0.019	0.063	20.09
$\left(J_t^{1/2}\right)^+$	0.129	0.064	36.04	0.143	0.070	12.03	0.163	0.079	2.81	0.182	0.086	1.91
J_t/RV_t	0.092	0.120	57.56	0.073	0.122	55.22	0.050	0.117	37.94	0.036	0.108	29.25
$(J_t/RV_t)^+$	0.209	0.091	3.87	0.247	0.089	2.85	0.295	0.089	0.87	0.337	0.089	0.94
JD	2.261	1.826	51.98	3.405	3.736	26.89	5.866	6.954	15.15	9.344	12.972	4.59
$JA>0$	0.125	0.061	7.26	0.141	0.067	3.58	0.158	0.077	1.54	0.175	0.080	0.55
$JA<0$	-0.133	0.066	6.54	-0.147	0.073	2.91	-0.168	0.081	1.37	-0.191	0.091	0.92

$U_{1,t}$												
α		**0.05**			**0.01**			**0.001**			**0.0001**	
N(Days)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)	N(J^+)	N(JA>0)	N(JA<0)
2,022	844	397	447	567	259	308	346	159	187	226	102	124
	MEAN	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**	**MEAN**	**SD**	**LB(10)**
J_t	0.009	0.022	7.42	0.007	0.021	7.02	0.005	0.020	8.03	0.004	0.020	6.94
J_t^+	0.021	0.029	5.73	0.026	0.034	2.69	0.031	0.040	0.66	0.038	0.047	0.82
$J_t^{1/2}$	0.055	0.077	13.37	0.040	0.075	20.42	0.027	0.068	21.55	0.020	0.062	17.48
$\left(J_t^{1/2}\right)^+$	0.131	0.065	27.90	0.144	0.070	10.34	0.159	0.078	1.86	0.176	0.085	2.21
J_t/RV_t	0.089	0.121	51.05	0.070	0.122	51.86	0.050	0.116	40.00	0.036	0.107	24.52
$(J_t/RV_t)^+$	0.213	0.091	3.97	0.249	0.091	2.56	0.291	0.092	0.90	0.326	0.094	1.20
JD	2.395	1.977	36.24	3.567	3.993	25.69	5.843	6.583	9.97	8.924	10.727	10.61
$JA>0$	0.126	0.062	8.42	0.140	0.066	4.79	0.151	0.073	0.52	0.168	0.079	0.42
$JA<0$	-0.135	0.067	5.60	-0.147	0.073	2.31	-0.166	0.082	0.91	-0.182	0.090	1.00

In order to assess the importance of this adjustment on jump detection and measurement and as a robustness exercise, the corresponding statistics for jump tests conducted using standard versions of realised bipower variation (BV_t) and tripower quarticity (TQ_t) are also calculated.These statistics are not reported in full in order to conserve space, however, important differences are explained where relevant.

The tables show statistics for a range of different series including the jump variation (J_t), the absolute value of actual jumps $(J_t^{1/2})$, and the relative contribution of jump variation to realised variation (J_t/RV_t). Statistics are also calculated for the corresponding series that include only those days identified as containing at least one significant jump $(J_t^+, (J_t^{1/2})^+ \text{ and } (J_t/RV_t)^+)$. The *JD* series measures jump duration and is defined as the number of days between significant jump days and *JA* refers to actual jumps. Following Andersen, Bollerslev, Frederiksen and Nielsen (2006), actual jumps are identified by attributing the sign of the largest return occurring during the day to the absolute value of the actual jump $(J_t^{1/2})$ and this provides a simple way to examine any notable differences between positive ($JA>0$) and negative ($JA<0$) jumps. Of course, this assumes implicitly that the largest return of the day is causing the jump. Along with descriptive statistics, the first row of the tables show the number of days identified as significant jump days $N(J^+)$ along with the number of days exhibiting positive ($N(JA>0)$) or negative ($N(JA<0)$) jumps.

Beginning with the EUR-USD contract presented in Table 4.4.4.1, the statistics provide many important results and patterns. First, each test detects fewer jumps as the significance level (α) declines, which is entirely expected as a smaller α implies a more stringent test for jumps. The important feature of this result, however, is to decide on the optimum level of α. Whilst using a small value for α in a conservative approach is expected to identify large jumps that occur less frequently, this approach is traded off against the view that such a conservative approach will not correctly identify small, genuine jumps that occur more frequently. The approach adopted in this chapter follows that of Andersen, Bollerslev and Diebold (2007b) in preferring a significance level of 0.001, which provides a compromise for this trade-off. However, as a robustness exercise and to assess the performance of test statistics across significance levels, each table reports statistics for a range of significance levels. Data for the EUR-USD shows that tests conducted using $Z_{1,t}$ find fewer jumps than those using $U_{1,t}$, which, in turn, find fewer jumps than tests using $W_{1,t}$. This confirms the results of Huang and Tauchen (2006) that $W_{1,t}$ tends to over reject the null in the right hand tail. For this reason, and in support of the findings of Andersen, Bollerslev and Dobrev (2007) and Huang and Tauchen (2006), this chapter prefers the use of $Z_{1,t}$ as the appropriate and more stringent jump test statistic. Adjusting for market microstructure noise effects by using the one period staggered version of realised bipower variation and tripower quarticity finds many more jumps than testing using the standard versions, which suggests that the presence of market microstructure frictions biases the tests against detecting jumps and this adjustment has a dramatic impact on the detection of daily jumps for the five-minute returns considered here.

Table 4.4.4.1 reveals the presence of many jumps, and far more than would be expected from a continuous price process (we expect 0.001 x 1,819=1.82 for α= 0.001). This shows that jumps are an important feature of the underlying price process and occur far more frequently than suggested by the parametric modelling literature. As expected, the mean jump variation (J_t) declines with α since there are more days signalled as non-jump days, whereas the average jump variation on only those days containing jumps (J_t^+) increases as α declines showing that, although fewer jump days are identified, they show on average a larger measure of jump variation. The average jump variation on jump days for EUR-USD is 0.113 for α=0.001. The corresponding average of the absolute value of the actual jump is 0.301 showing that the jumps are substantial. The average relative contribution of jump variation on jump days, $(J_t/RV_t)^+$, measuring the contribution of jump variation as a proportion of total variation, is 0.358 showing that, on average, jump variation contributes an influential 35.8% of return variation on these days. In identifying fewer jumps, the $Z_{1,t}$ statistic shows a longer average duration between jumps at 8.213 days (for α=0.001) as compared to the $U_{1,t}$ measure. This corresponds to approximately 30 jumps per year, which, even at such a conservative level of α, is far more than is identified in the parametric jump modelling literature. Positive jumps are on average larger than negative ones in absolute terms, but there is very little difference between these averages and very similar numbers of positive and negative jumps are identified. Finally, the LB(10) statistics represent the Ljung Box serial correlation test for up to ten lags and finds a small degree of serial correlation in the J_t and $J_t^{1/2}$ series, but far less serial correlation in the same series that include only significant jump days, suggesting that the size of jump variation and absolute actual jumps are not particularly correlated. Relative jump contribution and jump duration, however, show higher values of LB(10) suggesting that the contribution of jump variation to total variation and the timing of jumps are correlated over time, and more so than for the underlying jump variation and jump series.

Table 4.4.4.2 presents the same statistics for GBP-USD futures, which show similar characteristics. Fewer jumps are detected as α declines, under the $Z_{1,t}$ specification of the test and without adjusting for market microstructure noise. Employing the most stringent jump test under the $Z_{1,t}$ specification and for conservative levels of α generates far more jumps than would be expected from a continuous process, reinforcing the earlier evidence on EUR-USD that jumps are an important feature of the underlying price process. Indeed, GBP-USD shows the presence of many more jumps than EUR-USD. It is important to note that there are 119 more days in total in the sample for GBP-USD, nevertheless, the GBP-USD contract shows a higher proportion of days containing significant jumps than EUR-USD. Mean jump variation on significant jump days is 0.057 (under $Z_{1,t}$ for α=0.001) with absolute actual jumps measuring 0.226 on average, showing that although more jumps are detected for GBP-USD than EUR-USD, the jumps are slightly smaller but remain sizeable. Despite the jumps being smaller on average and causing lower variation, the relative contribution of jump variation to realised variation is higher for GBP-USD than EUR-USD at 36.40% on significant jump days, and this is due to both the occurrence of jumps and the smaller realised variation that is displayed for GBP-USD than EUR-USD. With more jumps detected for GBP-USD, it is no surprise that the average duration between them is shorter at 5.298, days corresponding to approximately 45 jumps per year. Again, this shows that jumps occur more frequently than is suggested by the parametric estimation literature. There is tentative evidence of asymmetry between positive and negative jumps for GBP-USD with more positive jumps detected, however, despite these numbers of jump days, the average size of the actual positive and negative jumps is almost identical in absolute terms. Finally, the LB(10) statistics are very high, and far higher for GBP-USD than EUR-USD, indicating a greater degree of serial correlation for the GBP-USD series. These statistics increase when considering actual jumps rather than jump variation, but they are dramatically lower when including only significant jump days, suggesting that the timing of jumps is relatively more serially correlated than the size of the jumps themselves. This is confirmed by the large Ljung-Box test statistic for jump duration (97.95), which suggests significant serial correlation in the intervals between significant jumps

To complete the analysis of the foreign exchange futures contracts, Tables 4.4.4.3 shows the relevant daily jump test summary statistics for JPY-USD futures. Similar patterns emerge across test statistics and significance levels in that the number of days containing jumps identified are smaller for $Z_{1,t}$ than $U_{1,t}$, which finds fewer jumps than $W_{1,t}$ especially for α lower than 0.05. Fewer jumps are identified as α becomes smaller and many more jumps are found when adjusting for the effects of market microstructure noise by using the one period staggered versions of realised bipower variation and tripower quarticity. Generally, there are more jumps found for JPY-USD than EUR-USD, but much less than for GBP-USD and, importantly, far more than would be expected from a continuous price process, confirming the importance and presence of jumps in the underlying price process. Again, selecting α=0.001 and $Z_{1,t}$ as the test statistic, the mean jump variation, absolute actual jump and relative jump contribution on significant jump days are 0.100, 0.281 and 35.0%, which are higher than the $U_{1,t}$ statistic for the same significance level. Fewer jumps are identified, but on average they are larger than those detected under $U_{1,t}$, which suggests that since the measure of jump variation is equivalent between the test statistics as the difference between realised variation and bipower variation, the $Z_{1,t}$ statistic performs relatively better in identifying only the days containing larger jumps. These means are considerably higher than the corresponding statistics for GBP-USD, but smaller than those for EUR-USD, except for the jump contribution which is similar to that for EUR-USD at 35%, suggesting that jump variation contributes on average a substantial 35% of total variation on average on significant jump days.

The duration between JPY-USD jump days is 8.146 days which is similar to that for EUR-USD and corresponds to approximately 29 jumps per year. More positive actual jumps are identified than negative actual jumps and their means are higher in absolute terms showing indications of asymmetry. Serial correlation is also present for the absolute jumps and relative jump contribution series according to the LB(10) statistics, but these are reduced drastically when selecting the series of significant jump days only. The timing of jumps shows serial correlation, as measured by the LB(10) statistic of 14.47 for the jump duration series.

In brief summary, therefore, jumps are present in the foreign exchange futures markets contained in this sample period, with the average relative contribution of jump variation to total variation on significant jump days of 35% for all three foreign exchange futures contracts showing an important contribution to total variation when jumps occur. Furthermore, serial correlation tests show stronger evidence that the timing and relative contribution of jumps are more correlated through time than the magnitude of the jump variation and absolute actual jumps.

Turning to the results for the equity market index futures contracts, Tables 4.4.4.4 to 4.4.4.6 show the summary statistics for the daily jump tests for the S&P 500 E-Mini, FTSE 100 and DJ Euro Stoxx 50 index futures. This consideration of the equity futures is particularly interesting given that they show much higher realised volatility than the foreign exchange futures considered previously. In support of the results documented for the foreign exchange futures markets, and as expected, the number of days detected containing statistically significant jumps decreases as the significance level becomes lower and therefore more stringent, but there are fewer jumps detected for equity index futures contracts, as measured by the proportion of days containing jumps, than foreign exchange futures contracts. Again the $Z_{I,t}$ statistic finds fewer jump days than the $U_{I,t}$ statistic, which, in turn, finds fewer daily jumps than the $W_{I,t}$ statistic, a result that enforces $Z_{I,t}$ as a more conservative test statistic and confirms previous evidence. However, in contrast to the foreign exchange futures contracts, jump detection procedures adjusted for market microstructure noise find fewer jumps than those which do not adjust for this distortion. Indeed, this is the only one of the nine contracts to find fewer jumps using staggered measures. Since staggering should remove the bias against finding jumps that market microstructure noise imparts on the jump test statistic, this result implies that this adjustment may be unnecessary for the S&P 500 E-Mini futures returns, and that adopting the five-minute frequency is sufficient to remove this noise.

The mean jump variation, absolute actual jump and relative jump contribution on significant jump days is 0.856, 0.669 and 32.7% respectively (for $Z_{I,t}$ and α=0.001). Despite finding fewer jump days for the S&P 500 E-Mini contract than the foreign exchange contracts, the average jump variation and absolute actual jumps are substantially higher indicating that the jumps detected are larger. The relative jump contribution on significant jump days of 32.7% is slightly smaller (approximately 3% smaller) for the S&P 500 E-Mini than the foreign exchange futures contracts, but it is important to note that average realised variation is much higher for the equity index future, which signals large jumps. Crucially, the jump tests at each significance level and under each different test statistic finds far more jump days than would be expected from a continuous price process showing that jumps are an important component of the underlying price process in terms of their presence, magnitude and contribution to total variation. With fewer jumps detected for the S&P 500 E-Mini contract than the foreign exchange futures for a similar sample size, it is not surprising that the average duration between jump days is longer for the equity contract at 18.767 days corresponding to approximately 13 jumps per year. The dynamic properties of the series shown by the LB(10) statistics show very little temporal dependence in the series including only jump days and slight serial correlation when considering the full series. This dependence is increased for the absolute actual jumps than the jump variation series. As found for the foreign exchange futures markets, serial correlation is high for the jump duration series indicating that the timing of jumps may be predictable even if their magnitudes are less dependent over time. Finally, there are slightly more positive jumps detected than negative jumps for the S&P 500 E-Mini futures and the absolute values of their means are higher showing possible indications of jump asymmetry, and the size of these average jumps in absolute terms is far higher than those for the foreign exchange market, which is particularly noteworthy.

In support of the results for the S&P 500 E-Mini futures contract, the results for the FTSE 100 future shown in Table 4.4.4.5 far more jump days than would be expected from a continuous process showing again that jumps are an integral component of the underlying price process. Although the FTSE 100 futures show more jump days than the S&P 500 E-Mini contract, there remains a fewer number of jump days than the foreign exchange futures for a similar sample size. For $Z_{I,t}$ and α=0.001, the mean jump variation, absolute actual jump and relative jump contribution on jump days is 0.351, 0.519 and 29.7% respectively. Despite identifying more jump days, these averages for the FTSE 100 futures are considerably lower than the corresponding averages for the S&P 500 E-Mini contract, implying smaller jumps on average. The averages are all larger than the foreign exchange markets, showing larger jumps on average, except for the relative jump contribution, which is lower at 29.7%. So, although the jumps are larger on average for the FTSE 100 contract, their average relative contribution to realised variation on significant jump days is lower. The average duration between jumps is 10.473 days indicating approximately 23 jumps per year, which is more than the E-Mini and similar to the EUR-USD and JPY-USD contracts, but smaller than the GBP-USD contract. There are slightly more positive actual jumps identified than negative actual jumps and the means of the negative jumps are larger in absolute terms. LB(10) statistics are generally higher for FTSE 100 futures than E-Mini futures, but display the same patterns. Specifically, there is evidence of serial correlation in the whole series, which strengthens when considering absolute actual jumps rather than jump variation, and these statistics are lower when focusing only on significant jump days. Jump durations are serially correlated, all of which imply that the timing of jumps are relatively more serially dependent than the measures of the actual jumps themselves.

Completing the analysis of the equity index futures markets, Table 4.4.4.6 shows the descriptive statistics for daily jump tests for the DJ Euro Stoxx 50 index futures. More jumps are detected using the one period staggered version of the tests, consistent with the three foreign exchange futures markets and the FTSE 100 contracts. Although the sample for DJ Euro Stoxx 50 futures contains a smaller number of days, the daily jump test statistics detect many more jumps than for both the S&P 500 E-Mini and the FTSE 100 markets. Again there are far more jump days detected than would be expected from a continuous price process revealing that jumps are an important component of the underlying price process. This is confirmed by the data presented in Table 4.4.4.6 where the average jump variation, absolute actual jumps and relative jump contribution on days containing significant jumps are 0.509, 0.574 and 29.3% respectively ($Z_{l,t}$, α=0.001). The averages of jump variation and absolute actual jumps are higher than the FTSE 100 and all three foreign exchange futures markets, but lower than the S&P 500 E-Mini contract. The average relative jump contribution of 29.3%, however, is similar in size to that of the FTSE 100 and lower than the other markets considered so far. Jumps in the DJ Euro Stoxx 50 futures market are detected frequently, specifically every 9.022 days on average, corresponding to approximately 28 jumps per year, and they are large in absolute terms causing large jump variation and contributing almost one third of total variation on jump days. There are more positive jumps than negative ones, but the negative jumps show a larger mean in absolute terms indicating the possibility of systematic asymmetry in the size and signs of jumps, or the presence of some extreme negative price movements. LB(10) statistics for DJ Euro Stoxx 50 futures are the highest of all equity index futures indicating serial dependence in the series. This dependence is greater for the whole series of jump variation rather than the sample of only significant jump days suggesting that the timing of jumps is important to their temporal dependence structure. When considering absolute actual jumps, the LB(10) statistics are higher in the sub sample of significant jump days, which suggests that the size of jumps may also be serially correlated. The large LB(10) statistic for jump duration is particularly noteworthy since it confirms that the intervals between jumps, and hence the jump timings, are correlated through time.

To conclude this description of the results, Tables 4.4.4.7 to 4.4.4.9 show the summary statistics for daily jump tests for the three interest rate futures markets. The results for the US 10-Year Treasury Bond in Table 4.4.4.7 show that this market exhibits very many jumps, similar in number to the GBP-USD market, but much more than the EUR-USD, JPY-USD and all the equity index futures markets. In support of previous findings, the staggered version of the tests finds more jumps than the standard version and $Z_{1,t}$ finds fewer jumps than $U_{1,t}$, which finds fewer jumps than $W_{1,t}$, with both patterns supported across all three interest futures markets. The average jump variation, absolute actual jumps and relative jump contribution for the US 10-Year T-Bond futures on days identified as containing a significant jump are 0.073, 0.227 and 39.0% respectively for $Z_{1,t}$ and α=0.001. Jump variations and actual jump sizes are therefore much larger than for the foreign exchange futures markets, but smaller than for the equity index futures markets. The relative jump contribution suggests that jump variation contributes 39.0% of total variation on average on significant jump days, which is a sizeable proportion and is the largest of all the markets considered in this study. These averages suggest that there are more jumps in the US 10-Year T-Bond market than the equity index markets, but of smaller magnitude, and there are more and larger jumps in the US 10-Year T-Bond market than in the foreign exchange market. The duration between jumps is 5.391 on average, amounting to approximately 44 jumps per year, which is much more frequent than the other markets except GBP-USD which shows a very similar duration. A greater incidence of negative jumps is countered by the higher mean actual positive jumps in absolute terms and may indicate the presence of some particularly large positive jumps. LB(10) statistics are higher for the full series than the jumps sub-sample and are higher for the absolute actual jump series than the jump variation series. More striking, however, are the large Ljung Box test statistics for the relative jump contribution and jump duration. All of these points suggest that there is some serial correlation in jump series that is driven by the timing of jumps rather than their magnitude.

The UK Gilt futures market is represented in Table 4.4.4.8 and shows the presence of many more jumps than the US 10-Year T-Bond futures but, in spite of this, Gilt futures show smaller average jump variations and absolute actual jumps on significant jump days than US 10-Year T-Bond futures, and also smaller than the equity and foreign exchange futures markets. Specifically, these averages are 0.043 and 0.186 for $Z_{1,t}$ and α=0.001. In addition, the mean relative contribution of jump variation to total variation on significant jump days of 30.9% is also relatively small with only the FTSE 100 and DJ Euro Stoxx 50 futures markets showing smaller contributions in the markets considered so far, although 30.9% is a sizeable contribution to total variation when jumps do occur. With so many jumps identified, it is no surprise that they occur more frequently and this is evidenced by the average duration of 4.262, amounting to about 57 jumps per year. There are more positive than negative actual jumps, but the mean of the negative actual jumps is higher in absolute terms suggesting that they exhibit more extreme price movements. Following the pattern of the other markets, the time series properties of the series show strongest evidence of serial correlation for the absolute actual jumps series and relative jump contributions that include the whole sample, and the jump durations, indicating that the timing of the jumps is a major driver of the serial dependence.

Finally, Table 4.4.4.9 shows the summary statistics for the daily jump tests for the Euro Bund interest rate futures contract. The data confirm the patterns identified previously regarding the number of jumps detected under various significance levels, test statistics and market microstructure noise adjustment. Despite containing the largest number of days in the sample (2,022), the Bund futures do not show as many jumps as the US 10-Year T-Bond or UK Gilt futures. However, it is important to note that many more jumps are identified than would be expected from a purely continuous process, confirming the importance of jumps in the price process. The mean jump variation, absolute actual jumps and relative jump contribution on significant jump days are 0.033, 0.163 and 29.5% respectively, which are all low compared to the other interest rate futures contracts considered, and indeed are the lowest of all markets in the study. Yet, the presence of jumps, their sizes and contribution to total variation emphasise the importance of jumps for the underlying price process. Average jump duration of 5.866 days corresponds to approximately 43 jumps per year and suggests that the jumps are regular and more frequent than for the foreign exchange or equity index futures markets. More negative actual jumps are identified than positive, with the negative ones showing a larger mean in absolute terms, but these means are low compared to all other futures markets. The time series statistics show the presence of serial correlation in the whole sample series as with most of the other markets. The higher LB(10) numbers for absolute actual jumps and relative jump contribution for the whole sample series compared with significant jump days series and jump duration suggests that the regularity and timing of jumps may be a crucial driver of this temporal dependence.

Further evidence on the presence, size and importance of jumps is provided in Figures 4.4.4.1 to 4.4.4.9, which plot realised volatility and three absolute actual jump series calculated from different significance levels. To maintain consistency, each plot uses the $Z_{J,t}$ test statistic, which incorporates the one period staggered measure of realised bipower variation and tripower quarticity, as guided by the results of Tables 4.4.4.1 to 4.4.4.9 and the existing literature. The lower three panels of each figure show the jump series in standard deviation form which measures the absolute value of the actual jumps across significance levels of 0.5, 0.001 and 0.0001 in order to examine the performance of the test against α.

Realised volatility for EUR-USD shown in Figure 4.4.4.1 is quite low generally. An episode of higher volatility is seen from 2000 to 2002 and again at the start of 2004, after which volatility is remarkably stable from mid 2004 until the end of the sample in mid 2006. The small fluctuations of realised volatility that occur from day-to-day are disrupted occasionally by particularly high volatility days or spikes and these are witnessed in early and mid 1999, most of 2000 and in the first half of 2004. The jumps in the second panel are calculated according to equation (4.15) and show very many small jumps. The larger jumps tend to coincide with days of high realised volatility and the extreme jumps also match the volatility spikes. However, although daily volatility spikes are associated with jumps, they do not always correspond to extreme jumps, showing that the continuous sample path remains an important driver of volatility.

Figure 4.4.4.1. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for EUR-USD Futures.

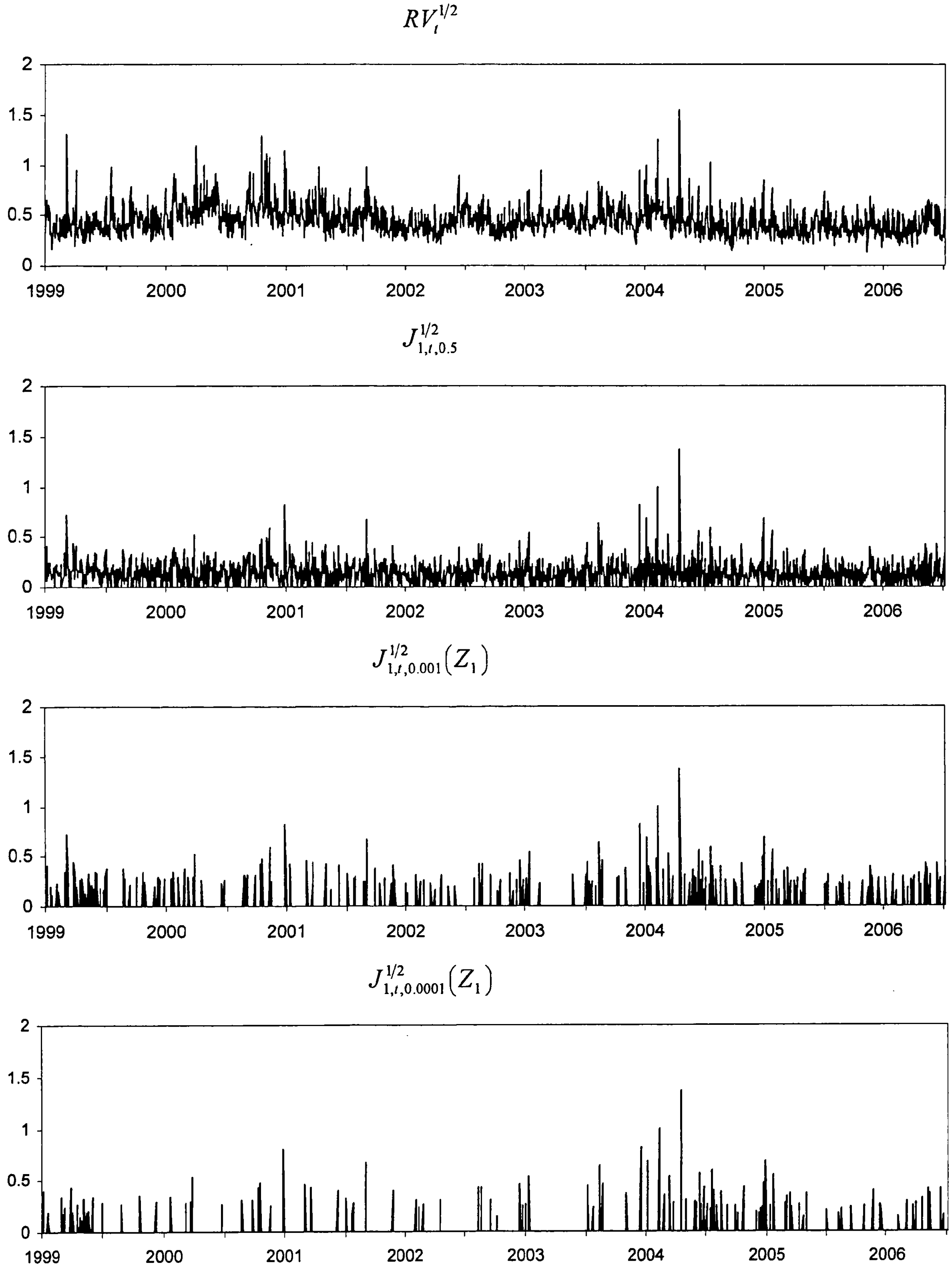


Figure 4.4.4.2. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for GBP-USD Futures.

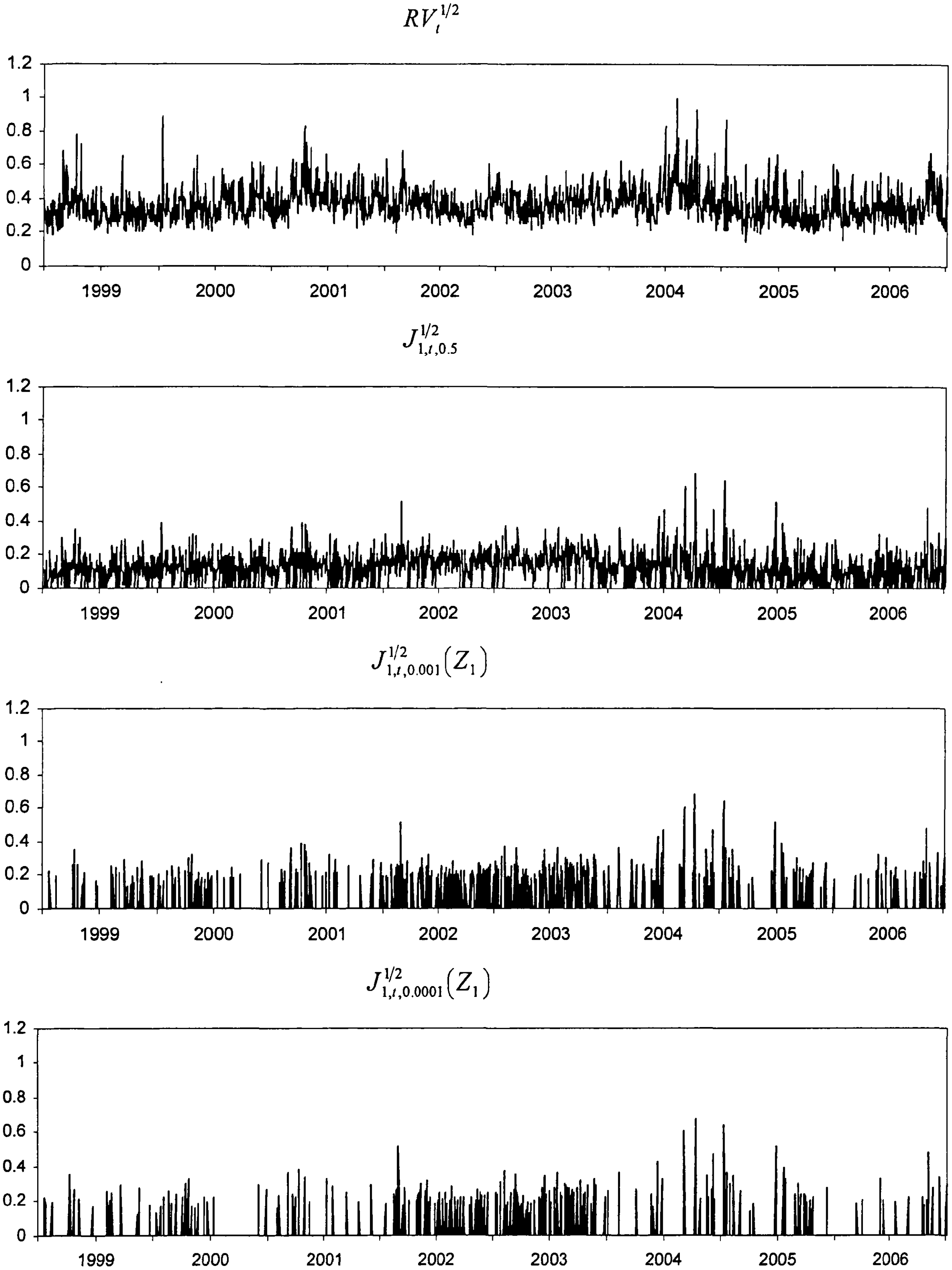


Figure 4.4.4.3. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for JPY-USD Futures.

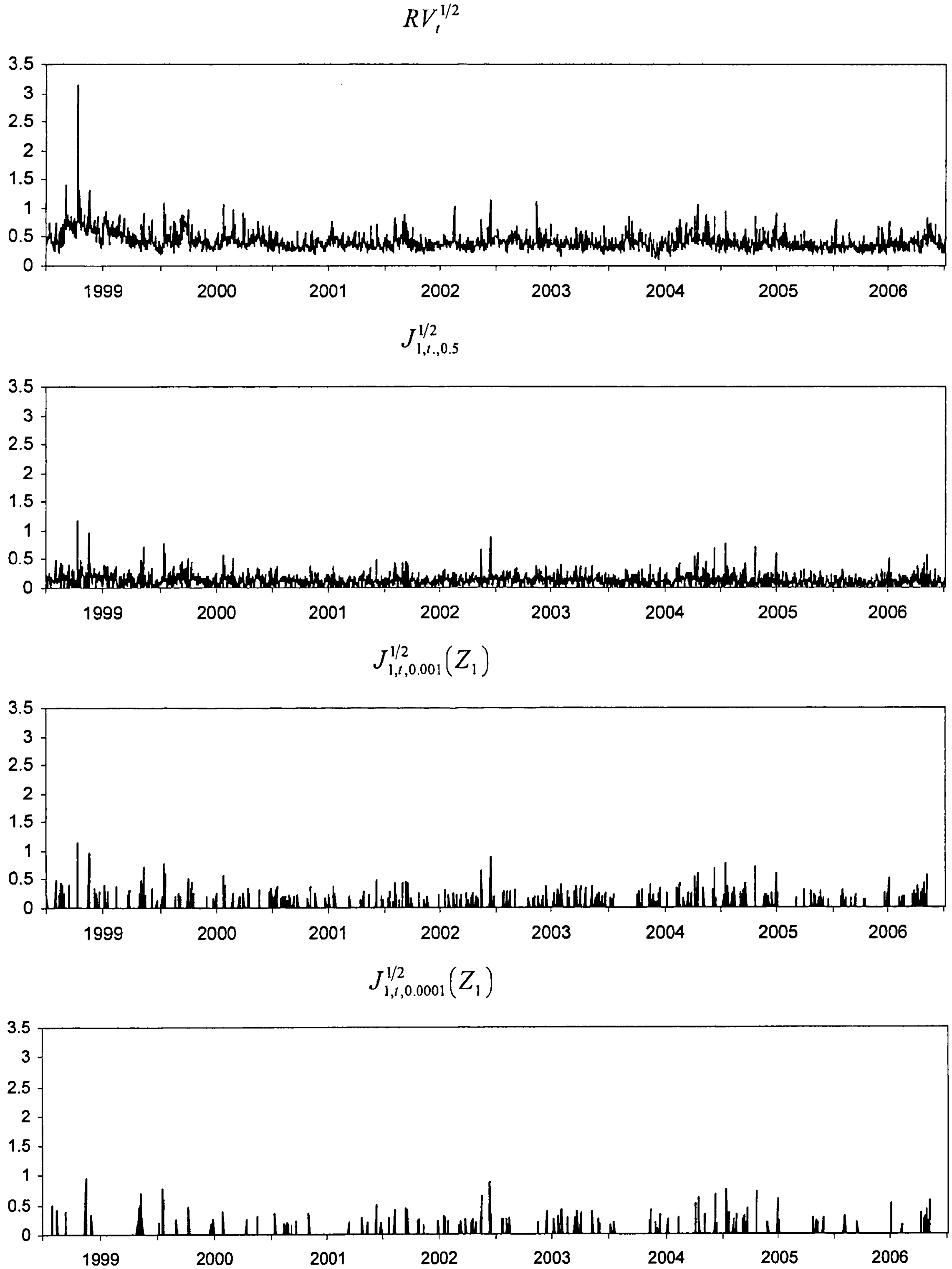


Figure 4.4.4.4. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for S&P 500 E-Mini Futures.

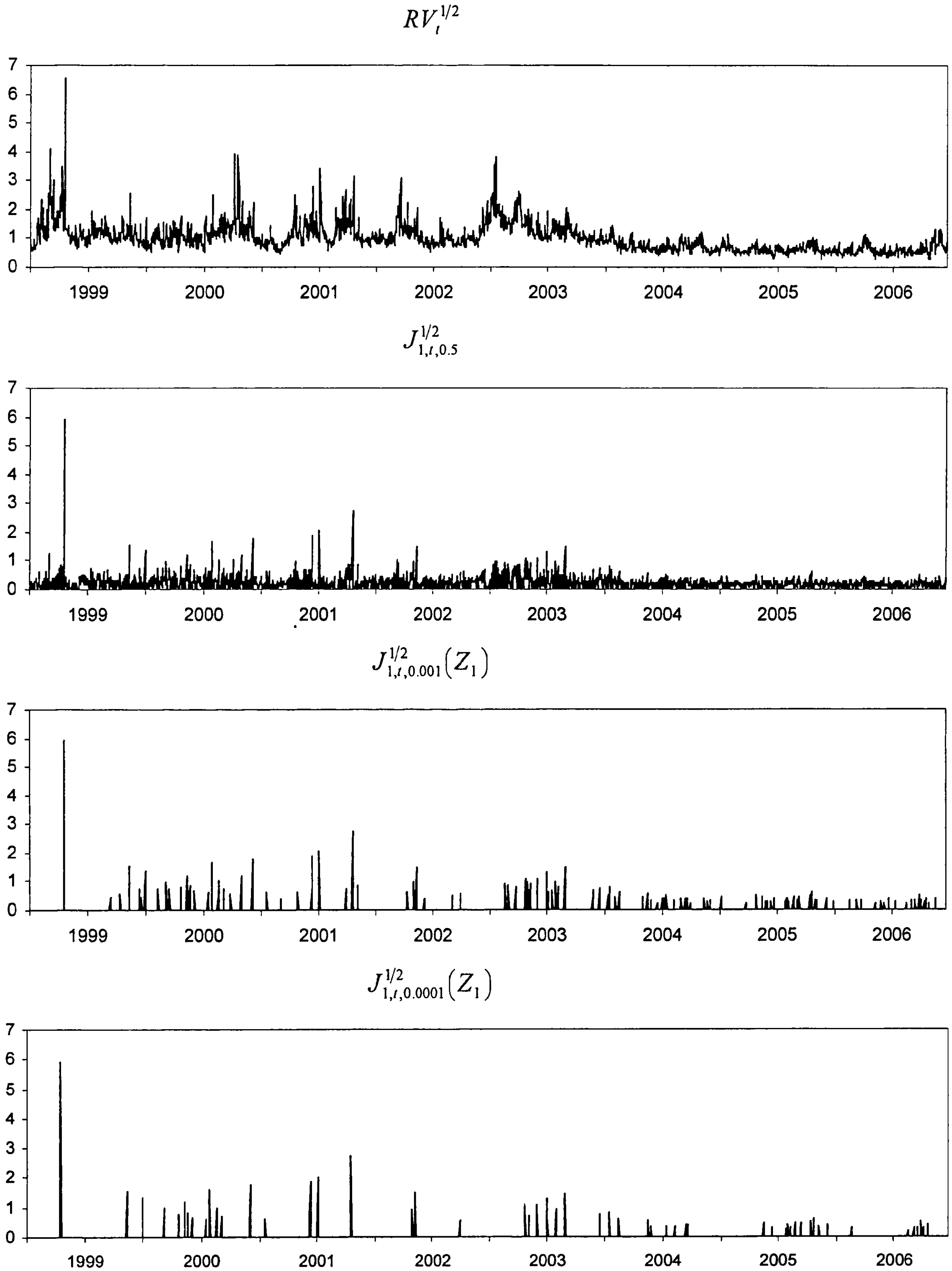


Figure 4.4.4.5. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for FTSE 100 Futures.

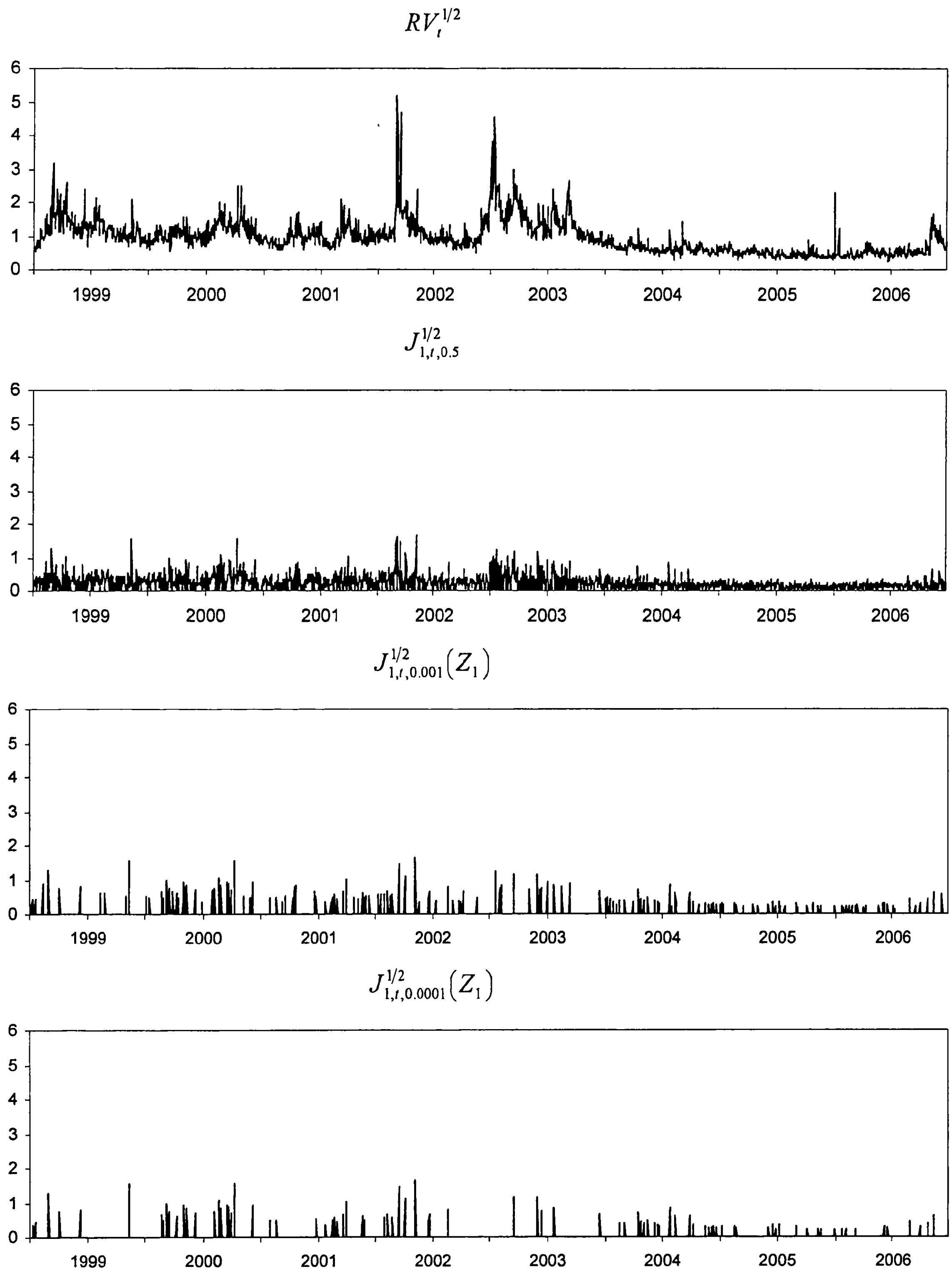


Figure 4.4.4.6. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for DJ Euro Stoxx 50 Futures.

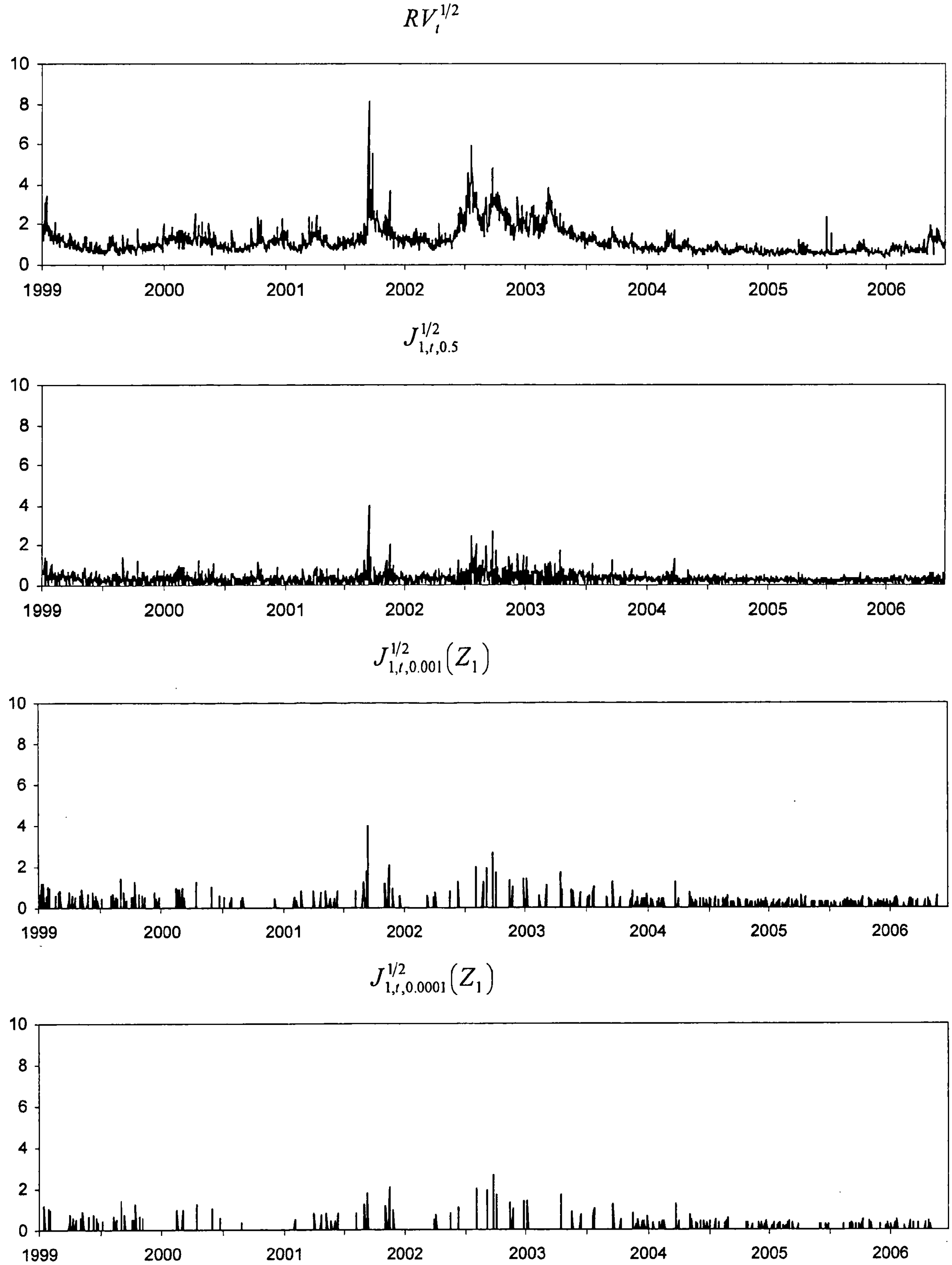


Figure 4.4.4.7. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for US 10-Year Treasury Bond Futures.

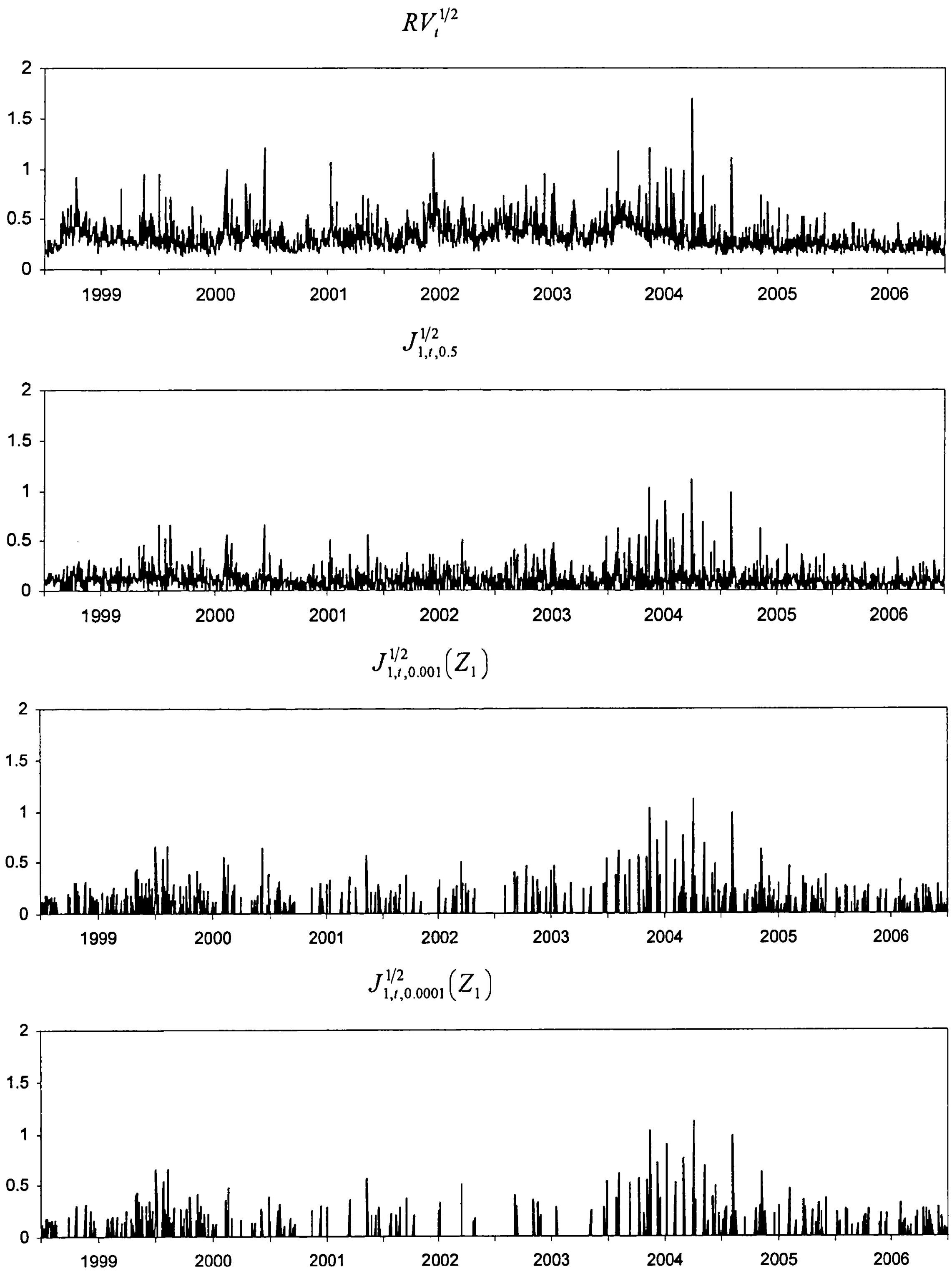


Figure 4.4.4.8. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for UK Gilt Futures.

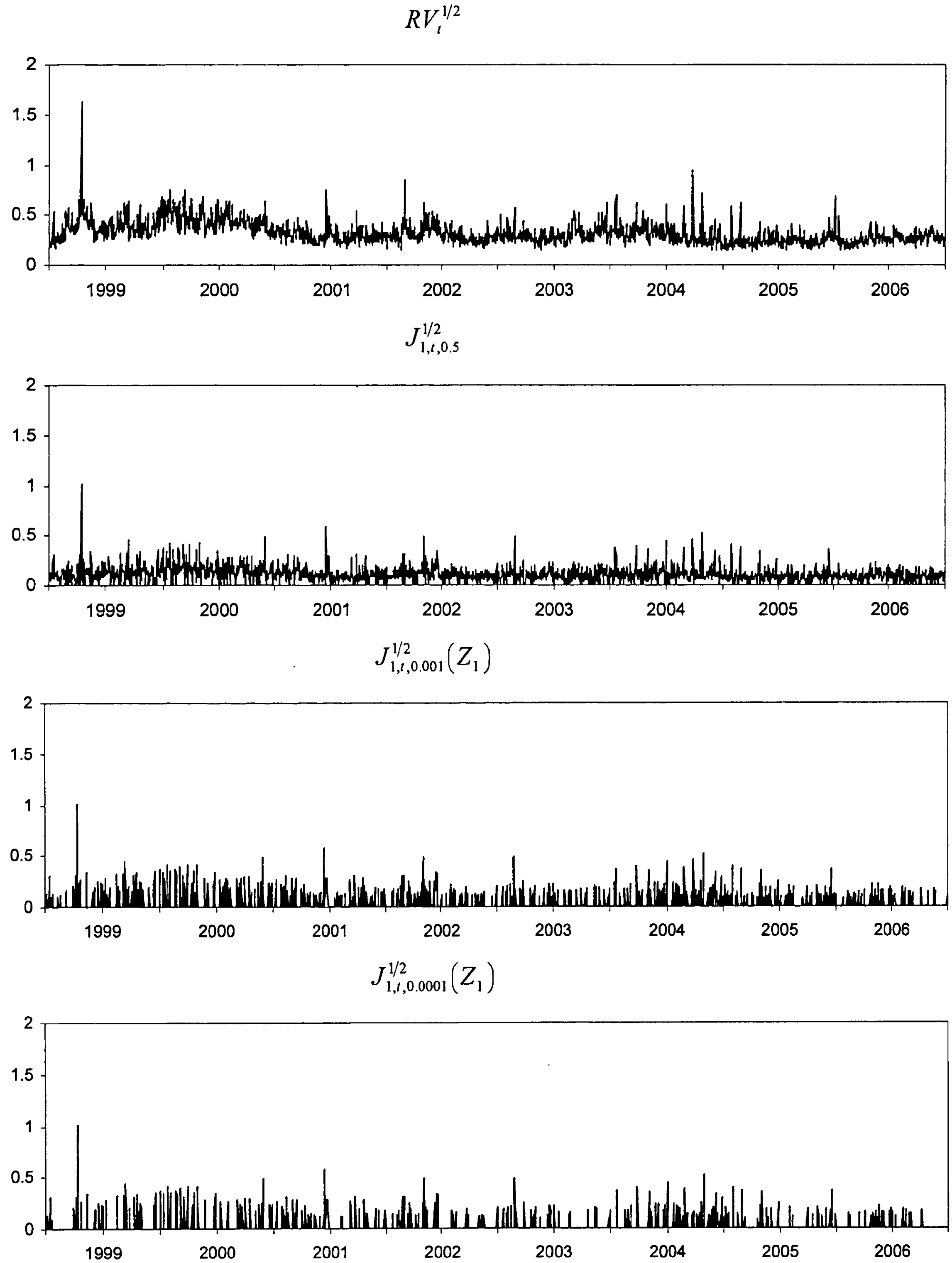
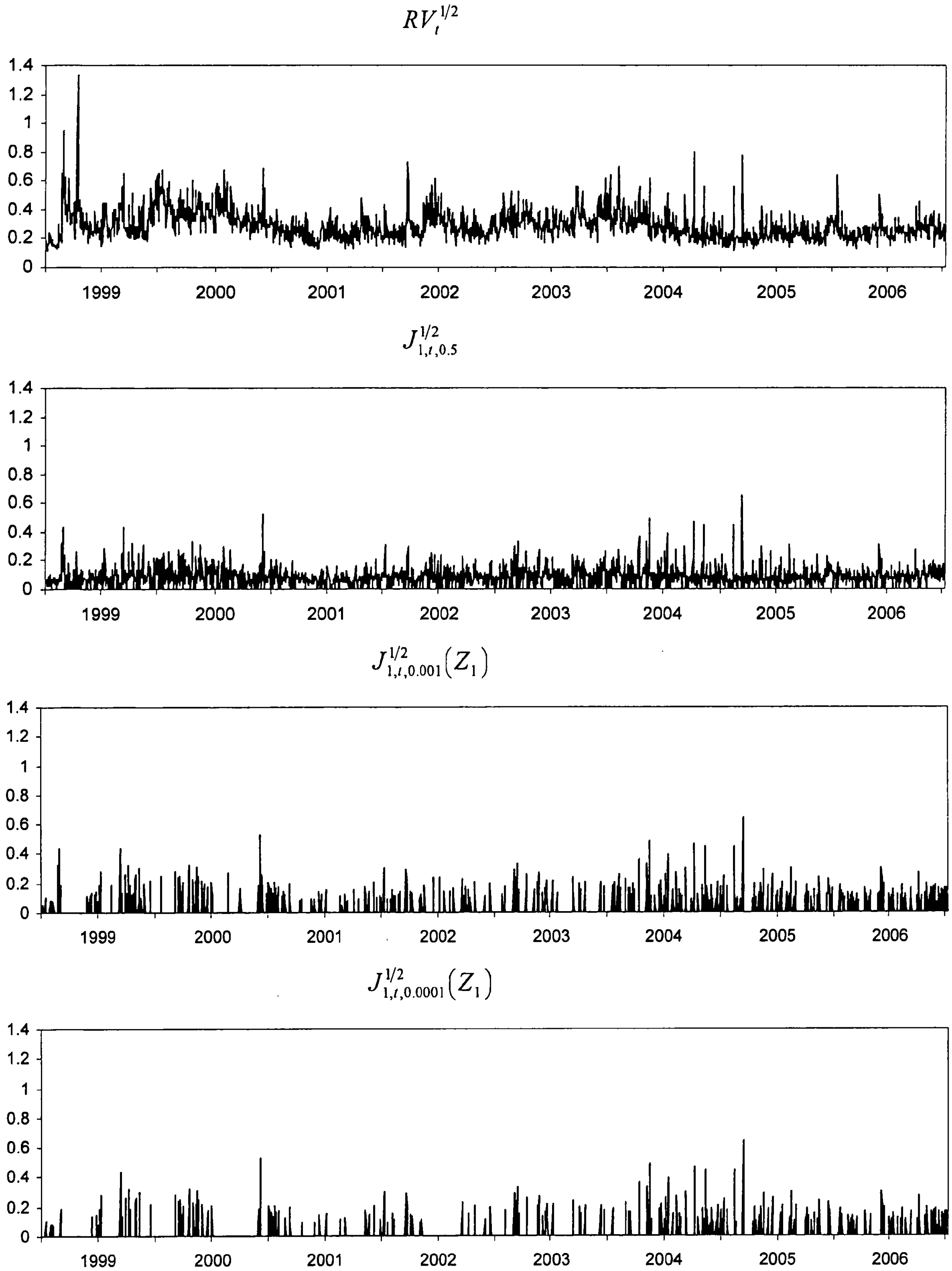


Figure 4.4.4.9. Daily Realised Volatility and Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for Euro Bund Futures.



The third panel of Figure 4.4.4.1 is of more interest since it shows the absolute actual jumps under the jump test specification ($Z_{I,t}$) and statistical significance level (0.001) that is preferred from the analysis of the descriptive statistics and previous literature. This plot shows that a fall in α to 0.001 finds far fewer jumps.

The jump measures on days showing significant jumps are equivalent for different values of α as measured by the square root of the difference between realised variation and staggered realised bipower variation, but the critical difference between the second and third plots is that far fewer days are identified as containing at least one jump, and those days that are identified show a more extreme difference between realised volatility and bipower variation. The impact of the lower α, therefore, and as expected, is to identify only larger jumps as significant jumps. For EUR-USD, jumps are high at the start of 1999, the end of 2000, beginning of 2001, end of 2003 and start of 2004. The interim periods show smaller jumps and the whole pattern appears to be cyclical such that the timings of peaks and troughs may be determined by business cycle fluctuations. There are many more jumps identified in the first half of 1999 and 2004 than in the other years of the sample, and these periods correspond to when realised volatility is high with coincident large spikes in volatility and particularly large jumps. In support of the statistics presented in Table 4.4.4.1, comparison of the plots of realised volatility and jumps reveals that, on significant jump days, jumps explain large proportions of realised volatility and this relative contribution appears to be higher on days showing higher volatility and particularly on days of volatility spikes. The final panel of Figure 4.4.4.1 shows the absolute actual jumps for α=0.0001. Fewer jump days are identified with this lower level of α, though most of the largest jumps are retained and more jumps are noticeable in early 1999 and mid 2004.

Plots for the GBP-USD futures contract are shown in Figures 4.4.4.2. Realised volatility, although lower than for the EUR-USD contract, shows similar patterns. More specifically, realised volatility is higher in the second half of 1998, a section of the sample that is unavailable for EUR-USD, otherwise volatility is higher in mid 1999, end of 2000 and 2004, which correspond to the timing of elevated volatility for EUR-USD. Volatility spikes are also present, but are not as extreme as those for EUR-USD, and are timed at late 1998, mid 1999, late 2000 and 2004. These spikes coincide with those of the EUR-USD contract, which may suggest some spillover or volatility transmission between markets. The jump series in the second panel for α=0.5 again shows a large number of small jumps and also a few larger jumps in 2004 particularly. The largest jumps correspond to realised volatility spikes, but the jumps are generally smaller than those for EUR-USD and do not appear to explain as much of the spikes as the EUR-USD jumps. Applying α=0.001 in the third panel of Figure 4.4.4.2 retains only the largest jumps and the plot shows the presence of many more jumps than for the corresponding plot for the EUR-USD contract. In particular, there are many jumps identified in 1999 and from mid 2000 to mid 2003, although these do not tend to be large. The largest jumps occur in 2004 as with the EUR-USD contract. The final panel of Figure 4.4.4.2 filters out yet more small jumps retaining only large differences between realised variation and bipower variation and especially those in 2004. Again there are a striking number of jump days during the two-year period from mid 2001 to mid 2003 even after implementing a more stringent significance level. A wave like pattern to jumps is also evident form the plots with peaks in late 1998, late 2000 and early 2001, mid 2004 and mid 2006, which correspond to those identified for EUR-USD futures.

Figure 4.4.4.3 shows plots of realised volatility and jumps for the JPY-USD futures contract. Realised volatility has a similar level to that of GBP-USD, but the plot is distorted somewhat by an extreme volatility spike in late 1998. Abstracting from this spike, volatility shows a very similar pattern to the other foreign exchange markets rising in late 1998, late 1999, early 2000 and 2004 and the amplitude of the fluctuation is wider than GBP-USD and similar to EUR-GBP. Volatility spikes are of similar magnitude to those for EUR-USD, except for the enormous spike in late 1998, with other particularly large spikes occurring in late 1998, late 1999, early 2000, 2002 and 2004. Interestingly, the large outstanding spike is not explained by the presence of an equally large jump showing that this day of elevated volatility is caused by continuous sample path volatility. The largest jumps do explain large proportions on other high volatility days. The third panel of Figure 4.4.4.3 shows the larger jumps more clearly and they are found to be of similar size to those of EUR-USD. Large jumps in late 1998, mid 1999, mid 2002 and 2004 are a recurring feature of the jump plots for all three of the foreign exchange futures contracts. Other critical features are the presence of very many jumps, even at low significance levels, and the high relative contribution of the larger jumps to days of particularly high realised volatility.

Realised volatility is far higher for the S&P 500 E-Mini futures contract than either of the foreign exchange contracts as shown by Figure 4.4.4.4. Abstracting from the wild fluctuations, the average realised volatility is higher and this is confirmed by the results shown in Tables 4.4.3.2 to 4.4.3.4. Volatility is particularly high during the second half of 1998, early 2000, late 2000, early 2001, late 2001 and mid to late 2002, which correspond to the previous discussion for foreign exchange contracts. In contrast to the currency futures, there is no elevated volatility in 2004 for the S&P 500 E-Mini contracts and volatility has been remarkably stable in this contract since mid 2003. The largest spike in realised volatility occurs in late 1998, coinciding with the extreme spike found for JPY-USD, and other huge volatility days are found in this same period and also 2000, 2001 and 2002. The absolute actual jumps shown in the second panel of Figure 4.4.4.4 shows a large number of jumps detected including some very small jumps. The large jump during the early part of the sample explains nearly all of the corresponding spike in realised volatility and other large jumps also coincide with high volatility days, however, they do not always contribute such a large proportion of the volatility.

Applying α=0.001 in the third panel of Figure 4.4.4.4 eliminates many of the small jumps from the second panel. This also shows relatively fewer jump days identified compared to the foreign exchange market and this confirms the evidence presented in Table 4.4.4.4. This panel also emphasises the magnitude of the larger jumps, particularly during the first half of the sample, which dwarf the majority of jumps measured for the foreign exchange market. For the latter part of the sample, jumps are present even though realised volatility is low and these jumps are smaller than in the earlier part of the sample, occur more frequently and are similar in size to those found for the foreign exchange markets. The bottom panel of figure 4.4.4.4 eliminates yet more of the smaller jumps leaving sporadic but particularly large jumps from the end of 1998 to early 2003.

Realised volatility for the FTSE 100 futures contract in Figure 4.4.4.5 shows a very similar pattern to that for the S&P 500 E-Mini. Volatility is generally higher than for the foreign exchange market and is similar in magnitude to the S&P 500 E-Mini. The pattern of volatility is strikingly similar to the S&P 500 E-Mini with periods of higher volatility in late 1998, early 2000, late 2001, late 2002 and early 2003. From mid 2003 onwards, volatility has been low and stable. The largest volatility spikes occur in late 2001, caused by the terrorist attacks in New York in

September of that year, and also in mid and late 2002, which coincide with the onset of conflict in Iraq. These periods of heightened FTSE 100 futures volatility match very closely the high volatility periods for the S&P 500 E-Mini, however, there are no such extreme spikes in late 2001 for the S&P 500 E-Mini since these important days are excluded from the sample as the S&P 500 E-Mini market was closed. Interestingly, the episodes of highest volatility, which may be speculated to correspond to times of geopolitical tension, do not give rise to particularly large jumps, as shown by the second panel of Table 4.4.4.5, suggesting that the volatility is caused by consecutive large price movements rather than isolated price jumps. The panel also shows many small jumps for α=0.5 and only very few dramatic jumps. The large jumps appear to be much smaller than the large jumps found in the E-Mini market. Small jumps are eliminated by using α=0.001 and 0.0001 in the bottom two panels of the figure. The FTSE 100 shows more jumps than the S&P 500 E-Mini, but of smaller size, and shows fewer jumps than the foreign exchange markets, but of larger size. Although there are occasional large jumps coinciding with high volatility, the relative contribution of significant jumps to total variation seems quite low and this is confirmed by the low average relative contribution statistics in Table 4.4.4.5.

To complete the consideration of the equity index markets, Figure 4.4.4.6 displays the plots of realised volatility and absolute actual jumps for the DJ Euro Stoxx 50 futures market. Volatility is quite high generally, and appears higher than for the other two equity index markets, as confirmed by the descriptive statistics of Table 4.4.3.3, although the magnitude of volatility is obscured in the plot by the very large spikes. It shows also a strikingly similar pattern to that of the S&P 500 E-Mini and FTSE 100 futures with higher volatility in early 1999, early 2000, late 2001, late 2002 and early 2003. Since mid 2003 volatility has been comparatively low and stable. The aforementioned terrorist events and war in Iraq generated tremendous stock market volatility in 2001, 2002 and 2003 and this volatility is not matched by the presence of extreme jumps. The second panel of Figure 4.4.4.6 shows many small jumps and many jumps similar in size to those of the previous five markets, which appear to explain large proportions of the volatility occurring on those days. The dramatic spikes in volatility, however, do give rise to extremely large jumps, but they are not sufficiently large to explain large proportions of the realised volatility. This is evidenced again in Table 4.4.4.6, where the relative contribution of jumps on significant jumps days is shown to be small for the DJ Euro Stoxx 50 market and smaller in comparison to the foreign exchange and interest rate futures markets. The advantage of viewing the volatility and jumps in the plots is that they show that although the relative contribution of jumps to total volatility is smaller for the equity index futures markets, it can be seen that this finding may be biased by the dramatic volatility found in the middle of the sample. Inspection of the first and last two-and-a-half years of the sample shows not only that many more jumps are identified, but that they also explain larger proportions of realised volatility, and this is particularly evident in the third and fourth panels of the figure. The jump tests therefore find more jumps, and measures them as more important in terms of their contribution to total variation, on days when realised volatility is at its average level. This also implies that the extreme volatility found in the equity markets has been caused mostly by long series of consecutive large price changes rather than isolated abrupt price movements.

Turning to the interest rate futures, Figure 4.4.4.7 shows the plots for the US 10-Year Treasury Bond futures contract. Realised volatility for this contract shows very similar levels and patterns to the foreign exchange futures contracts and the EUR-USD in particular. There are no extreme movements in volatility during 2001, 2002 and 2003 as witnessed in the equity index futures, but there are periods of higher volatility in late 1998, early 2000, late 2001 and late 2003. In addition to these elevated levels of volatility, there are many volatility spikes, particularly in early 2000, early and late 2001, and 2004, although they are not as dramatic in magnitude as the volatility spikes found for the equity index futures. The remaining panels of Figure 4.4.4.7 show that most volatility spikes correspond to large jumps, with these jumps explaining large proportions of this total volatility, a finding which is supported by the average relative jump contribution in Table 4.4.4.7. Many small jumps are eliminated by using α=0.001 and 0.0001 in the bottom two panels, yet these still show the presence of many jumps, particularly in the first and last thirds of the sample. The largest jumps occur in 1999, 2003 and 2004 confirming the previous results for the foreign exchange futures.

The UK Gilt future shows the lowest volatility of all markets considered so far, as illustrated by Figure 4.4.4.8. There are very few departures from this low volatility and any such spikes are small in relation to the average volatility and in comparison to the other markets. The single most dramatic spike occurs in late 1998, which supports the finding of a similarly timed spike in most other markets considered and the EUR-USD, JPY-USD and S&P 500 E-Mini contracts in particular. The second panel shows that this spike in volatility is also associated with a jump, and the jump contributes approximately two thirds of this total volatility. This panel also shows a large number of small jumps with any sizeable jump corresponding to a volatility spike and explaining a large proportion of it. Adopting a conservative statistical significance level of 0.001 in the third panel retains the largest jumps, but also shows the presence of many more jumps than the corresponding plot for other futures markets, which confirms the statistics provided in Table 4.4.4.8. The UK Gilt shows the largest number of jumps of all markets, but they tend to be smaller in comparison and the majority of the largest jumps are clustered in 1999 and 2004.

Finally, Figure 4.4.4.9 shows the realised volatility and daily absolute actual jump plots for the Euro Bund futures market. The realised volatility plot shows a similar pattern over the sample to the other interest rate and foreign exchange futures markets. Volatility is low for the Bund, even lower than for the Gilt, trending higher in late 1998, late 1999, late 2001 and late 2003. Extreme volatility days are found in late 1998, 1999, late 2001 and 2004, most of which correspond to days showing the presence of one or more jump. Interestingly, the largest volatility spike in the sample for the Bund occurs in late 1998, but is not explained by the presence of a jump. More encouragingly, the vast majority of the other volatility spikes constitute a large contribution from jumps. Such large jumps remain in the third and fourth panels of Figure 4.4.4.9 showing that altering the significance levels concentrates the jump detection procedure on finding larger discrepancies between realised volatility and bipower variation.

In concluding this section, Tables 4.4.4.1 to 4.4.4.9 and Figures 4.4.4.1 to 4.4.4.9 all confirm the presence of numerous jumps in futures markets across a range of asset classes, statistical significance levels and test specifications. In addition, the absolute values of jumps are often large in magnitude, occur frequently and regularly, and contribute heavily to realised volatility, particularly on days exhibiting very high volatility. Jumps, therefore, represent a critical component of the underlying price process, and this chapter aims to investigate further some of the economic reasons for their existence. The sample period shows interesting patterns in the volatility and jump series, which are confirmed across all nine markets, and the remainder of this chapter will explore in more detail the specific nature of this pattern and its relationship to underlying macroeconomic factors and news. It is interesting that the equity index futures show a slightly different volatility pattern to the foreign exchange and interest rate futures markets in displaying extremely high volatility in late 2001, 2002 and 2003, which are not explained by the presence of jumps. The inclusion of this extreme volatility tends to overshadow the size and contribution of jumps in these markets, and emphasises that jumps are not always the main driver of high volatility. Perhaps more informative in this regard, and as a first step towards examining the determinants and causes of jumps, the following section pinpoints the exact timing of these jumps by making use of the high frequency data available for this study in testing for and measuring intraday jumps.

4.4.5 Intraday Jumps

In this section, intraday jumps occurring during interval k are detected and measured through the method proposed by Andersen, Bollerslev and Dobrev (2007), which is formalised by

$$\kappa_k(\Delta) = r_{t+k\cdot\Delta,\Delta} \cdot I\left[\left|r_{t+k\cdot\Delta,\Delta}\right| > \Phi_{1-\beta/2} \cdot \sqrt{\Delta \cdot BV_{t+1}(\Delta)}\right], \qquad k = 1,2,\ldots,\frac{1}{\Delta}, \qquad (4.36)$$

where $\beta = 1-(1-\alpha)^{\Delta}$ such that α defines the significance level of the test. Tables 4.4.5.1 to 4.4.5.9 report the basic summary statistics for various related series.[22] Following Andersen, Bollerslev, Frederiksen and Nielsen (2006), the tables report summary statistics for the absolute value of intraday jumps $\left(|\kappa_k|\right)$ series along with the series that includes only those five-minute intervals during which significant intraday jumps occurred $\left(|\kappa_k|^{+}\right)$. The analysis presented here also attempts to identify potential asymmetry between positive (κ_k^{+}) and negative (κ_k^{-}) jumps and aims to examine the contribution of these intraday jumps to realised volatility. Whilst this method detects the returns causing intraday jumps, the jump variation associated with these individual jumps is measured as

$$JV_{t,k} = r_k^2 - \left(\Delta \cdot BV_{t+1}\right). \qquad (4.39)$$

[22] Since the intraday jumps are so far apart when using five-minute returns, the Ljung-Box test for serial correlation is not instructive for standard lag lengths and so is not calculated here.

Table 4.4.5.1. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for EUR-USD Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	997	487	510	775	571	275	296	501	357	170	187	326
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.002	0.022	1.379	0.000	0.001	0.019	1.379	0.000	0.001	0.017	1.379	0.000
$\lvert\kappa_k\rvert^+$	0.237	0.111	1.379	0.051	0.272	0.126	1.379	0.099	0.306	0.139	1.379	0.103
κ_k^+	0.242	0.117	0.948	0.051	0.280	0.134	0.948	0.126	0.318	0.149	0.948	0.127
κ_k^-	-0.231	0.105	-0.085	-1.379	-0.265	0.118	-0.099	-1.379	-0.296	0.129	-0.103	-1.379
$JV_{t,k}^+$	0.066	0.096	1.894	0.002	0.087	0.120	1.894	0.009	0.111	0.144	1.894	0.010
$JV_{t,k}^+/RV_t$	0.226	0.100	0.843	0.058	0.276	0.105	0.843	0.091	0.321	0.108	0.843	0.096
JVD_t^+/RV_t	0.291	0.137	0.882	0.111	0.314	0.129	0.882	0.159	0.351	0.122	0.882	0.179

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	803	410	393	667	462	236	226	410	272	138	134	248
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.019	1.379	0.000	0.001	0.016	1.379	0.000	0.001	0.014	1.379	0.000
$\lvert\kappa_k\rvert^+$	0.227	0.124	1.379	0.052	0.255	0.139	1.379	0.052	0.284	0.158	1.379	0.073
κ_k^+	0.229	0.132	0.948	0.059	0.263	0.148	0.948	0.073	0.291	0.166	0.948	0.073
κ_k^-	-0.224	0.115	-0.052	-1.379	-0.247	0.128	-0.052	-1.379	-0.277	0.149	-0.081	-1.379
$JV_{t,k}^+$	0.064	0.106	1.894	0.002	0.082	0.131	1.894	0.002	0.103	0.161	1.894	0.005
$JV_{t,k}^+/RV_t$	0.210	0.119	0.843	0.033	0.252	0.129	0.843	0.056	0.291	0.140	0.843	0.056
JVD_t^+/RV_t	0.253	0.148	0.882	0.051	0.284	0.154	0.882	0.065	0.319	0.155	0.882	0.067

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	783	402	381	651	439	225	214	394	252	124	128	234
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.019	1.379	0.000	0.001	0.016	1.379	0.000	0.000	0.013	1.379	0.000
$\lvert\kappa_k\rvert^+$	0.226	0.123	1.379	0.052	0.254	0.136	1.379	0.052	0.276	0.150	1.379	0.073
κ_k^+	0.227	0.131	0.948	0.059	0.261	0.144	0.948	0.073	0.279	0.155	0.948	0.073
κ_k^-	-0.224	0.113	-0.052	-1.379	-0.246	0.127	-0.052	-1.379	-0.273	0.145	-0.081	-1.379
$JV_{t,k}^+$	0.064	0.106	1.894	0.002	0.080	0.130	1.894	0.002	0.096	0.159	1.894	0.005
$JV_{t,k}^+/RV_t$	0.211	0.116	0.843	0.033	0.250	0.125	0.843	0.056	0.284	0.129	0.843	0.067
JVD_t^+/RV_t	0.254	0.145	0.882	0.051	0.278	0.147	0.882	0.065	0.305	0.144	0.882	0.067

Table 4.4.5.2. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for GBP-USD Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	1,067	543	524	812	592	303	289	503	350	169	181	311
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.016	0.749	0.000	0.001	0.013	0.749	0.000	0.000	0.011	0.749	0.000
$\lvert\kappa_k\rvert^+$	0.176	0.073	0.749	0.062	0.200	0.083	0.749	0.070	0.221	0.095	0.749	0.084
κ_k^+	0.178	0.079	0.749	0.063	0.203	0.091	0.749	0.070	0.226	0.111	0.749	0.084
κ_k^-	-0.175	0.066	-0.062	-0.720	-0.197	0.073	-0.075	-0.720	-0.217	0.078	-0.088	-0.720
$JV_{t,k}^+$	0.035	0.042	0.554	0.004	0.045	0.053	0.554	0.005	0.057	0.065	0.554	0.007
$JV_{t,k}^+/RV_t$	0.200	0.087	0.761	0.051	0.242	0.095	0.761	0.069	0.279	0.105	0.761	0.100
JVD_t^+/RV_t	0.263	0.118	0.804	0.109	0.284	0.116	0.804	0.091	0.314	0.115	0.804	0.150

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	1,031	534	497	792	564	282	282	479	331	163	168	291
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.015	0.749	0.000	0.001	0.012	0.749	0.000	0.000	0.010	0.749	0.000
$\lvert\kappa_k\rvert^+$	0.163	0.076	0.749	0.055	0.179	0.087	0.749	0.063	0.199	0.098	0.749	0.063
κ_k^+	0.164	0.081	0.749	0.056	0.183	0.097	0.749	0.063	0.205	0.113	0.749	0.063
κ_k^-	-0.162	0.069	-0.055	-0.720	-0.174	0.076	-0.066	-0.720	-0.193	0.082	-0.078	-0.720
$JV_{t,k}^+$	0.031	0.042	0.554	0.003	0.038	0.054	0.554	0.004	0.048	0.066	0.554	0.004
$JV_{t,k}^+/RV_t$	0.178	0.100	0.761	0.031	0.207	0.111	0.761	0.042	0.241	0.122	0.761	0.047
JVD_t^+/RV_t	0.232	0.128	0.804	0.044	0.244	0.132	0.804	0.051	0.274	0.136	0.804	0.076

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	1,014	532	482	783	520	259	261	442	303	149	154	262
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.015	0.749	0.000	0.001	0.012	0.749	0.000	0.000	0.010	0.749	0.000
$\lvert\kappa_k\rvert^+$	0.165	0.073	0.749	0.062	0.184	0.084	0.749	0.063	0.204	0.097	0.749	0.063
κ_k^+	0.167	0.079	0.749	0.062	0.187	0.094	0.749	0.063	0.208	0.110	0.749	0.063
κ_k^-	-0.162	0.066	-0.062	-0.720	-0.181	0.073	-0.071	-0.720	-0.200	0.082	-0.082	-0.720
$JV_{t,k}^+$	0.031	0.042	0.554	0.003	0.039	0.053	0.554	0.004	0.049	0.066	0.554	0.004
$JV_{t,k}^+/RV_t$	0.181	0.095	0.761	0.042	0.217	0.106	0.761	0.047	0.250	0.118	0.761	0.047
JVD_t^+/RV_t	0.235	0.125	0.804	0.060	0.255	0.125	0.804	0.067	0.290	0.131	0.804	0.088

Table 4.4.5.3. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for JPY-USD Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	948	512	436	789	522	282	240	465	300	166	134	284
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.019	0.989	0.000	0.001	0.017	0.989	0.000	0.001	0.014	0.989	0.000
$\lvert\kappa_k\rvert^+$	0.222	0.113	0.989	0.076	0.256	0.130	0.989	0.092	0.292	0.143	0.989	0.110
κ_k^+	0.228	0.118	0.949	0.076	0.264	0.133	0.949	0.092	0.303	0.139	0.889	0.111
κ_k^-	-0.215	0.106	-0.076	-0.989	-0.247	0.126	-0.094	-0.989	-0.278	0.148	-0.110	-0.989
$JV_{t,k}^+$	0.060	0.087	0.971	0.005	0.080	0.109	0.971	0.008	0.103	0.127	0.971	0.012
$JV_{t,k}^+/RV_t$	0.219	0.096	0.782	0.082	0.266	0.106	0.782	0.082	0.314	0.116	0.782	0.132
JVD_t^+/RV_t	0.263	0.125	0.873	0.104	0.298	0.126	0.873	0.146	0.332	0.126	0.873	0.185

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	820	450	370	696	428	231	197	391	230	125	105	219
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.018	0.989	0.000	0.001	0.015	0.989	0.000	0.000	0.013	0.989	0.000
$\lvert\kappa_k\rvert^+$	0.217	0.122	0.989	0.043	0.252	0.142	0.989	0.075	0.295	0.165	0.989	0.076
κ_k^+	0.222	0.126	0.949	0.043	0.257	0.146	0.949	0.092	0.304	0.164	0.949	0.111
κ_k^-	-0.212	0.116	-0.048	-0.989	-0.246	0.138	-0.075	-0.989	-0.284	0.166	-0.076	-0.989
$JV_{t,k}^+$	0.060	0.094	0.971	0.002	0.081	0.119	0.971	0.005	0.111	0.151	0.971	0.005
$JV_{t,k}^+/RV_t$	0.206	0.113	0.782	0.028	0.255	0.128	0.782	0.064	0.305	0.143	0.782	0.093
JVD_t^+/RV_t	0.243	0.140	0.873	0.059	0.279	0.146	0.873	0.072	0.320	0.154	0.873	0.093

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	814	449	365	688	425	227	198	385	233	128	105	221
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.018	0.989	0.000	0.001	0.015	0.989	0.000	0.000	0.013	0.989	0.000
$\lvert\kappa_k\rvert^+$	0.218	0.121	0.989	0.043	0.252	0.141	0.989	0.075	0.292	0.164	0.989	0.094
κ_k^+	0.222	0.126	0.949	0.043	0.259	0.145	0.949	0.076	0.300	0.163	0.949	0.111
κ_k^-	-0.212	0.116	-0.048	-0.989	-0.245	0.137	-0.075	-0.989	-0.282	0.165	-0.094	-0.989
$JV_{t,k}^+$	0.060	0.094	0.971	0.002	0.081	0.119	0.971	0.005	0.109	0.150	0.971	0.008
$JV_{t,k}^+/RV_t$	0.208	0.111	0.782	0.028	0.257	0.125	0.782	0.064	0.304	0.140	0.782	0.093
JVD_t^+/RV_t	0.246	0.139	0.873	0.063	0.284	0.142	0.873	0.088	0.321	0.150	0.873	0.093

Table 4.4.5.4. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for S&P 500 E-Mini Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	697	363	334	586	365	195	170	330	190	94	96	183
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.002	0.035	5.584	0.000	0.001	0.031	5.584	0.000	0.001	0.028	5.584	0.000
$\lvert\kappa_k\rvert^+$	0.457	0.354	5.584	0.118	0.548	0.444	5.584	0.144	0.682	0.561	5.584	0.207
κ_k^+	0.451	0.390	5.584	0.135	0.538	0.493	5.584	0.154	0.684	0.659	5.584	0.226
κ_k^-	-0.464	0.310	-0.118	-2.884	-0.560	0.382	-0.144	-2.884	-0.680	0.449	-0.207	-2.884
$JV_{t,k}^+$	0.324	1.320	31.105	0.013	0.486	1.804	31.105	0.020	0.765	2.465	31.105	0.042
$JV_{t,k}^+/RV_t$	0.191	0.088	0.862	0.062	0.237	0.100	0.862	0.115	0.289	0.114	0.862	0.115
JVD_t^+/RV_t	0.228	0.115	0.925	0.114	0.262	0.117	0.925	0.130	0.300	0.123	0.925	0.165

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	591	290	301	501	299	137	162	276	187	82	105	180
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.032	5.584	0.000	0.001	0.028	5.584	0.000	0.001	0.026	5.584	0.000
$\lvert\kappa_k\rvert^+$	0.420	0.389	5.584	0.076	0.513	0.500	5.584	0.078	0.577	0.592	5.584	0.078
κ_k^+	0.425	0.436	5.584	0.076	0.535	0.588	5.584	0.078	0.646	0.720	5.584	0.078
κ_k^-	-0.416	0.337	-0.088	-2.884	-0.495	0.412	-0.089	-2.884	-0.523	0.464	-0.089	-2.884
$JV_{t,k}^+$	0.316	1.435	31.105	0.004	0.501	1.995	31.105	0.004	0.669	2.498	31.105	0.004
$JV_{t,k}^+/RV_t$	0.162	0.114	0.862	0.013	0.204	0.136	0.862	0.018	0.232	0.151	0.862	0.021
JVD_t^+/RV_t	0.191	0.140	0.925	0.013	0.221	0.147	0.925	0.021	0.241	0.158	0.925	0.021

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	551	258	293	471	273	119	154	252	159	67	92	155
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.031	5.584	0.000	0.001	0.027	5.584	0.000	0.000	0.025	5.584	0.000
$\lvert\kappa_k\rvert^+$	0.411	0.397	5.584	0.076	0.495	0.514	5.584	0.078	0.590	0.631	5.584	0.078
κ_k^+	0.417	0.458	5.584	0.076	0.533	0.629	5.584	0.078	0.667	0.791	5.584	0.078
κ_k^-	-0.406	0.336	-0.088	-2.884	-0.466	0.404	-0.089	-2.884	-0.533	0.481	-0.089	-2.884
$JV_{t,k}^+$	0.316	1.486	31.105	0.004	0.498	2.083	31.105	0.004	0.732	2.702	31.105	0.004
$JV_{t,k}^+/RV_t$	0.161	0.114	0.862	0.015	0.200	0.138	0.862	0.018	0.235	0.158	0.862	0.021
JVD_t^+/RV_t	0.189	0.140	0.925	0.015	0.216	0.153	0.925	0.018	0.241	0.168	0.925	0.021

Table 4.4.5.5. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for FTSE 100 Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	835	407	428	697	447	225	222	407	264	129	135	251
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\|\kappa_k\|$	0.002	0.029	3.108	0.000	0.001	0.025	3.108	0.000	0.001	0.022	3.108	0.000
$\|\kappa_k\|^+$	0.403	0.257	3.108	0.090	0.463	0.299	3.108	0.106	0.533	0.333	3.108	0.107
κ_k^+	0.393	0.251	1.666	0.090	0.453	0.285	1.666	0.106	0.522	0.300	1.666	0.107
κ_k^-	-0.413	0.262	-0.098	-3.108	-0.473	0.313	-0.120	-3.108	-0.544	0.363	-0.140	-3.108
$JV_{t,k}^+$	0.220	0.449	9.439	0.008	0.294	0.587	9.439	0.011	0.384	0.725	9.439	0.011
$JV_{t,k}^+/RV_t$	0.168	0.072	0.670	0.050	0.206	0.079	0.670	0.079	0.243	0.083	0.670	0.135
JVD_t^+/RV_t	0.201	0.098	0.831	0.088	0.226	0.096	0.831	0.123	0.256	0.097	0.831	0.135

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	588	288	300	495	300	137	163	270	156	72	84	145
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\|\kappa_k\|$	0.001	0.023	3.108	0.000	0.001	0.019	3.108	0.000	0.000	0.016	3.108	0.000
$\|\kappa_k\|^+$	0.356	0.270	3.108	0.062	0.409	0.322	3.108	0.083	0.480	0.396	3.108	0.090
κ_k^+	0.339	0.243	1.649	0.062	0.374	0.275	1.517	0.087	0.440	0.337	1.517	0.100
κ_k^-	-0.373	0.294	-0.083	-3.108	-0.439	0.356	-0.083	-3.108	-0.514	0.439	-0.090	-3.108
$JV_{t,k}^+$	0.191	0.501	9.439	0.001	0.262	0.663	9.439	0.002	0.375	0.890	9.439	0.006
$JV_{t,k}^+/RV_t$	0.136	0.097	0.670	0.002	0.163	0.114	0.670	0.003	0.197	0.134	0.670	0.010
JVD_t^+/RV_t	0.162	0.120	0.831	0.002	0.181	0.129	0.831	0.003	0.212	0.147	0.831	0.010

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\|\kappa_k\|^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	538	260	278	457	255	122	133	235	133	56	77	125
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\|\kappa_k\|$	0.001	0.023	3.108	0.000	0.000	0.018	3.108	0.000	0.000	0.015	3.108	0.000
$\|\kappa_k\|^+$	0.368	0.275	3.108	0.067	0.422	0.320	3.108	0.101	0.494	0.395	3.108	0.104
κ_k^+	0.350	0.245	1.649	0.067	0.382	0.261	1.517	0.101	0.460	0.321	1.517	0.111
κ_k^-	-0.385	0.299	-0.090	-3.108	-0.458	0.363	-0.104	-3.108	-0.520	0.441	-0.104	-3.108
$JV_{t,k}^+$	0.203	0.521	9.439	0.004	0.271	0.702	9.439	0.009	0.389	0.946	9.439	0.010
$JV_{t,k}^+/RV_t$	0.146	0.094	0.670	0.016	0.179	0.108	0.670	0.025	0.222	0.122	0.670	0.058
JVD_t^+/RV_t	0.172	0.118	0.831	0.021	0.195	0.124	0.831	0.025	0.236	0.139	0.831	0.064

Table 4.4.5.6. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for DJ Euro Stoxx 50 Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	859	440	419	704	463	231	232	415	279	138	141	262
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.002	0.038	5.541	0.000	0.001	0.033	5.541	0.000	0.001	0.029	5.541	0.000
$\lvert\kappa_k\rvert^+$	0.487	0.360	5.541	0.101	0.580	0.424	5.541	0.133	0.661	0.486	5.541	0.166
κ_k^+	0.460	0.311	2.034	0.101	0.549	0.357	2.034	0.133	0.604	0.386	2.034	0.166
κ_k^-	-0.516	0.403	-0.101	-5.541	-0.611	0.480	-0.133	-5.541	-0.717	0.563	-0.194	-5.541
$JV_{t,k}^+$	0.354	1.158	30.210	0.010	0.501	1.540	30.210	0.017	0.657	1.943	30.210	0.027
$JV_{t,k}^+/RV_t$	0.163	0.082	0.861	0.068	0.202	0.093	0.861	0.099	0.237	0.103	0.861	0.114
JVD_t^+/RV_t	0.199	0.104	0.861	0.082	0.225	0.105	0.861	0.104	0.253	0.109	0.861	0.122

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	575	269	306	478	293	126	167	261	170	72	98	157
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.030	5.541	0.000	0.001	0.026	5.541	0.000	0.000	0.023	5.541	0.000
$\lvert\kappa_k\rvert^+$	0.443	0.394	5.541	0.055	0.532	0.491	5.541	0.101	0.615	0.573	5.541	0.101
κ_k^+	0.414	0.322	2.034	0.055	0.507	0.402	2.034	0.101	0.566	0.438	1.987	0.101
κ_k^-	-0.469	0.447	-0.083	-5.541	-0.550	0.549	-0.105	-5.541	-0.651	0.655	-0.111	-5.541
$JV_{t,k}^+$	0.340	1.377	30.210	0.002	0.509	1.900	30.210	0.009	0.688	2.443	30.210	0.010
$JV_{t,k}^+/RV_t$	0.145	0.108	0.861	0.016	0.179	0.126	0.861	0.029	0.209	0.141	0.861	0.041
JVD_t^+/RV_t	0.174	0.126	0.861	0.029	0.201	0.137	0.861	0.029	0.226	0.150	0.861	0.047

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	561	263	298	476	269	117	152	244	155	66	89	144
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.030	5.541	0.000	0.001	0.025	5.541	0.000	0.000	0.018	2.745	0.000
$\lvert\kappa_k\rvert^+$	0.439	0.391	5.541	0.055	0.523	0.495	5.541	0.101	0.560	0.408	2.745	0.101
κ_k^+	0.409	0.313	2.034	0.055	0.495	0.402	2.034	0.101	0.548	0.412	1.987	0.101
κ_k^-	-0.467	0.448	-0.101	-5.541	-0.545	0.556	-0.105	-5.541	-0.569	0.407	-0.111	-2.745
$JV_{t,k}^+$	0.334	1.392	30.210	0.002	0.504	1.972	30.210	0.009	0.467	0.813	7.441	0.010
$JV_{t,k}^+/RV_t$	0.144	0.105	0.861	0.016	0.176	0.126	0.861	0.029	0.200	0.134	0.861	0.047
JVD_t^+/RV_t	0.170	0.122	0.861	0.029	0.194	0.137	0.861	0.029	0.215	0.148	0.861	0.047

Table 4.4.5.7. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for US 10-Year Treasury Bond Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	920	444	476	735	596	292	304	513	419	209	210	377
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.018	1.457	0.000	0.001	0.017	1.457	0.000	0.001	0.016	1.457	0.000
$\lvert\kappa_k\rvert^+$	0.194	0.133	1.457	0.049	0.225	0.148	1.457	0.055	0.254	0.163	1.457	0.055
κ_k^+	0.195	0.131	0.954	0.055	0.224	0.145	0.954	0.055	0.248	0.158	0.954	0.055
κ_k^-	-0.193	0.135	-0.049	-1.457	-0.225	0.152	-0.058	-1.457	-0.260	0.167	-0.065	-1.457
$JV_{t,k}^+$	0.054	0.117	2.102	0.002	0.071	0.141	2.102	0.003	0.089	0.164	2.102	0.003
$JV_{t,k}^+/RV_t$	0.253	0.142	0.884	0.052	0.307	0.149	0.884	0.053	0.354	0.153	0.884	0.076
JVD_t^+/RV_t	0.316	0.169	0.892	0.107	0.356	0.163	0.892	0.107	0.394	0.158	0.892	0.107

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	630	295	335	518	358	172	186	312	235	107	128	205
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.015	1.457	0.000	0.001	0.014	1.457	0.000	0.000	0.012	1.457	0.000
$\lvert\kappa_k\rvert^+$	0.191	0.146	1.457	0.043	0.227	0.169	1.457	0.055	0.251	0.188	1.457	0.078
κ_k^+	0.193	0.147	0.954	0.043	0.229	0.168	0.954	0.070	0.255	0.187	0.954	0.082
κ_k^-	-0.189	0.146	-0.044	-1.457	-0.225	0.171	-0.055	-1.457	-0.248	0.190	-0.078	-1.457
$JV_{t,k}^+$	0.056	0.136	2.102	0.002	0.078	0.172	2.102	0.003	0.096	0.200	2.102	0.006
$JV_{t,k}^+/RV_t$	0.246	0.164	0.884	0.023	0.300	0.175	0.884	0.042	0.341	0.183	0.884	0.068
JVD_t^+/RV_t	0.300	0.186	0.892	0.062	0.344	0.191	0.892	0.068	0.390	0.192	0.892	0.107

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	587	268	319	477	321	151	170	279	213	96	117	188
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.014	1.457	0.000	0.000	0.012	1.457	0.000	0.000	0.011	1.457	0.000
$\lvert\kappa_k\rvert^+$	0.183	0.142	1.457	0.043	0.215	0.165	1.457	0.055	0.237	0.185	1.457	0.070
κ_k^+	0.185	0.139	0.954	0.043	0.212	0.161	0.954	0.063	0.234	0.180	0.954	0.078
κ_k^-	-0.181	0.144	-0.044	-1.457	-0.216	0.168	-0.055	-1.457	-0.240	0.190	-0.070	-1.457
$JV_{t,k}^+$	0.052	0.134	2.102	0.002	0.072	0.171	2.102	0.003	0.089	0.203	2.102	0.005
$JV_{t,k}^+/RV_t$	0.232	0.157	0.884	0.023	0.283	0.167	0.884	0.042	0.319	0.174	0.884	0.068
JVD_t^+/RV_t	0.286	0.184	0.892	0.062	0.326	0.188	0.892	0.068	0.361	0.185	0.892	0.119

Table 4.4.5.8. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for UK Gilt Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	1,435	680	755	1,037	880	425	455	710	581	283	298	497
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.012	0.788	0.000	0.001	0.011	0.788	0.000	0.000	0.010	0.788	0.000
$\lvert\kappa_k\rvert^+$	0.142	0.074	0.788	0.037	0.161	0.084	0.788	0.052	0.179	0.094	0.788	0.055
κ_k^+	0.141	0.072	0.618	0.050	0.160	0.082	0.618	0.052	0.179	0.091	0.618	0.055
κ_k^-	-0.142	0.075	-0.037	-0.788	-0.162	0.086	-0.052	-0.788	-0.180	0.098	-0.061	-0.788
$JV_{t,k}^+$	0.025	0.039	0.608	0.001	0.032	0.048	0.608	0.003	0.040	0.057	0.608	0.003
$JV_{t,k}^+/RV_t$	0.166	0.088	0.742	0.033	0.200	0.097	0.742	0.066	0.232	0.105	0.742	0.077
JVD_t^+/RV_t	0.229	0.130	0.858	0.090	0.248	0.128	0.858	0.110	0.271	0.130	0.858	0.121

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	1,190	542	648	905	674	316	358	565	421	198	223	370
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.011	0.788	0.000	0.000	0.010	0.788	0.000	0.000	0.008	0.788	0.000
$\lvert\kappa_k\rvert^+$	0.134	0.080	0.788	0.037	0.154	0.093	0.788	0.037	0.172	0.101	0.788	0.037
κ_k^+	0.135	0.080	0.618	0.037	0.155	0.091	0.618	0.045	0.175	0.096	0.526	0.051
κ_k^-	-0.133	0.081	-0.037	-0.788	-0.153	0.096	-0.037	-0.788	-0.170	0.106	-0.037	-0.788
$JV_{t,k}^+$	0.024	0.042	0.608	0.001	0.031	0.054	0.608	0.001	0.039	0.060	0.608	0.001
$JV_{t,k}^+/RV_t$	0.152	0.102	0.742	0.025	0.185	0.116	0.742	0.033	0.216	0.128	0.742	0.033
JVD_t^+/RV_t	0.200	0.135	0.858	0.035	0.220	0.140	0.858	0.037	0.246	0.151	0.858	0.059

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	1,144	520	624	882	639	303	336	540	390	178	212	345
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\kappa_k\rvert$	0.001	0.011	0.788	0.000	0.000	0.009	0.788	0.000	0.000	0.008	0.749	0.000
$\lvert\kappa_k\rvert^+$	0.136	0.080	0.788	0.037	0.155	0.093	0.788	0.037	0.170	0.097	0.749	0.037
κ_k^+	0.137	0.079	0.618	0.044	0.155	0.090	0.618	0.051	0.172	0.097	0.526	0.051
κ_k^-	-0.135	0.080	-0.037	-0.788	-0.155	0.096	-0.037	-0.788	-0.169	0.097	-0.037	-0.749
$JV_{t,k}^+$	0.024	0.043	0.608	0.001	0.032	0.054	0.608	0.001	0.038	0.055	0.555	0.001
$JV_{t,k}^+/RV_t$	0.154	0.100	0.742	0.025	0.188	0.113	0.742	0.033	0.218	0.123	0.742	0.033
JVD_t^+/RV_t	0.200	0.133	0.858	0.045	0.222	0.137	0.858	0.065	0.246	0.145	0.858	0.075

Table 4.4.5.9. Summary Statistics for Intraday Jumps Using $BV_{1,t}$ for Euro Bund Futures.

Raw Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	1,316	618	698	989	790	362	428	658	534	239	295	463
	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN
$\lvert\kappa_k\rvert$	0.001	0.010	0.613	0.000	0.000	0.009	0.613	0.000	0.000	0.008	0.613	0.000
$\lvert\kappa_k\rvert^+$	0.126	0.066	0.613	0.035	0.146	0.074	0.613	0.046	0.161	0.079	0.613	0.046
κ_k^+	0.122	0.065	0.574	0.035	0.142	0.073	0.574	0.046	0.160	0.079	0.574	0.046
κ_k^-	-0.129	0.068	-0.035	-0.613	-0.149	0.076	-0.052	-0.613	-0.162	0.079	-0.052	-0.613
$JV_{t,k}^+$	0.020	0.029	0.375	0.001	0.026	0.036	0.375	0.002	0.031	0.040	0.375	0.002
$JV_{t,k}^+/RV_t$	0.162	0.090	0.777	0.056	0.199	0.099	0.777	0.074	0.232	0.105	0.777	0.075
JVD_t^+/RV_t	0.215	0.128	0.909	0.075	0.239	0.130	0.909	0.092	0.267	0.133	0.909	0.103

Returns Standardised by Average Absolute Returns

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	960	421	539	758	539	241	298	458	339	156	183	298
	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN
$\lvert\kappa_k\rvert$	0.000	0.009	0.613	0.000	0.000	0.007	0.613	0.000	0.000	0.007	0.613	0.000
$\lvert\kappa_k\rvert^+$	0.125	0.075	0.613	0.016	0.144	0.084	0.613	0.017	0.163	0.093	0.613	0.017
κ_k^+	0.122	0.075	0.574	0.016	0.144	0.084	0.574	0.017	0.160	0.092	0.574	0.017
κ_k^-	-0.127	0.075	-0.025	-0.613	-0.145	0.084	-0.033	-0.613	-0.165	0.094	-0.035	-0.613
$JV_{t,k}^+$	0.021	0.033	0.375	0.000	0.027	0.040	0.375	0.000	0.035	0.048	0.375	0.000
$JV_{t,k}^+/RV_t$	0.155	0.110	0.777	0.004	0.191	0.124	0.777	0.010	0.228	0.133	0.777	0.010
JVD_t^+/RV_t	0.196	0.142	0.909	0.006	0.225	0.152	0.909	0.022	0.259	0.159	0.909	0.031

Returns Standardised by Standard Deviation

α	0.01				0.001				0.0001			
	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$	$N(\lvert\kappa_k\rvert^+)$	$N(\kappa_k^+)$	$N(\kappa_k^-)$	$N(JVD^+)$
	918	400	518	732	498	226	272	430	318	147	171	284
	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN
$\lvert\kappa_k\rvert$	0.000	0.008	0.613	0.000	0.000	0.007	0.613	0.000	0.000	0.006	0.613	0.000
$\lvert\kappa_k\rvert^+$	0.125	0.073	0.613	0.017	0.144	0.083	0.613	0.017	0.162	0.090	0.613	0.035
κ_k^+	0.123	0.074	0.574	0.017	0.143	0.083	0.574	0.017	0.159	0.091	0.574	0.055
κ_k^-	-0.126	0.073	-0.025	-0.613	-0.145	0.082	-0.035	-0.613	-0.164	0.090	-0.035	-0.613
$JV_{t,k}^+$	0.020	0.033	0.375	0.000	0.027	0.040	0.375	0.000	0.034	0.047	0.375	0.001
$JV_{t,k}^+/RV_t$	0.154	0.107	0.777	0.004	0.193	0.121	0.777	0.010	0.225	0.127	0.777	0.036
JVD_t^+/RV_t	0.194	0.140	0.909	0.025	0.223	0.147	0.909	0.031	0.252	0.152	0.909	0.036

The resulting daily contribution of intraday jumps is calculated as

$$JVD_{t,k} = \sum_{k=1}^{1/\Delta} JV_{t,k} \,. \tag{4.40}$$

The performance of the intraday detection technique is examined over a range of statistical significance levels and the effect of market microstructure noise is mitigated by replacing BV_t with $BV_{1,t}$ in equations (4.36) and (4.39). The method relies on volatility remaining constant throughout the day; however, the evidence of Chapter 3 combined with the existing literature show that periodic intraday volatility patterns are commonly observed in studies using high frequency data. In order to investigate the impact of departures from this assumption, intraday jumps are detected and measured for the raw five-minute returns and also for returns standardised by average intraday absolute returns and return standard deviation, representing two alternative measures of, and methods for annihilating, the intraday volatility pattern.[23] Finally, the tables also display the number of intraday jumps identified $\left(N\left(|\kappa_k|^+\right)\right)$, the number of positive $\left(N\left(\kappa_k^+\right)\right)$ and negative $\left(N\left(\kappa_k^-\right)\right)$ jumps and the number of days identified as having one or more jumps $\left(N\left(JVD^+\right)\right)$.

Table 4.4.5.1 shows the summary statistics for intraday jumps for the EUR-USD futures contract. Andersen, Bollerslev and Dobrev (2007) advocate the use of a conservative significance level of α=0.001 for the daily jump test and show that this intraday jump technique outperforms the daily jump measures in identifying days containing jumps. The discussion in this section follows that approach in adopting this same significance level, but the tables show the summary statistics for tests performed at significance levels 0.01 and 0.0001 for comparison. The intraday jump test performed on raw returns for α=0.001 in the top panel of Table 4.4.5.1 shows 501 days containing at least one jump, which is substantially more days than identified by the daily jump test in Table 4.4.4.1, where 222, 251 and 323 days were found to contain at least one jump according to the $Z_{1,t}$, $U_{1,t}$ and $W_{1,t}$ test statistics respectively. Furthermore, there are 571 intraday jumps detected in total meaning that there are some days containing more than one intraday jump. There are more

[23] Although there are more sophisticated techniques to adjust for the intraday volatility pattern, as described in Chapter 3, this chapter maintains a strictly non-parametric approach to the identification of jumps.

negative jumps discovered than positive jumps and the staggered version of the test identifies 11 more days containing jumps than the standard version and 17 more jumps in total, although results from the latter standard version are not tabulated here.

The mean absolute jump when including all returns in the series is 0.001, whilst the mean absolute jump including only the five-minute intervals containing jumps is 0.272. Positive jumps are 0.280 on average and negative ones are smaller on average in absolute terms with a mean of -0.265. Jumps range from -1.379 to 0.948, which represent the minimum and maximum returns of the sample as shown in Table 4.4.3.1, and the ranges between the minimum and maximum positive and negative jumps show that, as expected, only sizeable returns of either sign are identified as intraday jumps. The average jump variation offered by individual intraday jumps of 0.087 is only slightly smaller than the average daily jump variation of 0.093 shown in Table 4.4.4.1 and ranges from 0.009 to 1.894. Individual intraday jumps contribute an average of 27.6% of the total variation of the days on which they occur, which rises to 31.4% when combining the jump variation contributed by multiple jumps on some days. This relative daily jump variation contribution to realised variation ranges from 15.9% to 88.2%. These statistics suggest that large five-minute returns may be identified as jumps and these jumps are capable of producing a very high jump variation component to total variation, which contribute very heavily to this realised variation. By reducing the significance level of the test, fewer intraday jumps are detected; means, standard deviations and relative jump contributions are all higher, and minimum and maximum ranges show that the largest returns are retained as intraday jumps.

The data in the second panel of Table 4.4.5.1 performs the intraday jump detection procedure on returns that have been standardised by the intraday volatility pattern measured by the average absolute return of each five-minute interval. Annihilating the intraday volatility pattern reduces the number of days containing at least one jump by 91 and detects 109 fewer intraday jumps in total. The mean jumps are lower (in absolute terms) than those detected for raw returns, the standard deviations are higher, maximum values show that the largest returns are still identified as jumps, and the minimum values show that large negative returns are also identified as jumps. The drop in means can therefore be explained by the identification of fewer jumps, which include at least some small returns identified as jumps. The corresponding measures of jump variation show the same patterns with lower jump values explaining lower proportions of realised variation. Standardisation of returns by intraday return standard deviation as an alternative measure of the intraday volatility pattern reduces the number of intraday jumps identified even further by 23 jumps and 16 days. Despite reducing the number of jumps identified, the statistics in the bottom panel of Table 4.4.5.1 are very similar to those of the second panel showing that the descriptive statistics do not change substantially between the standardisation techniques.

Table 4.4.5.2 displays the summary statistics for GBP-USD. This shows a similar number of days containing at least one jump (503) and total number of intraday jumps (592) as the EUR-USD contract, despite containing a larger number of days in the sample. Importantly, and in confirmation of the EUR-USD results, this intraday jump detection procedure identifies far more days containing at least one jump than the daily jump detection technique of section 4.4.4. Again, there are some days containing more than one jump, but slightly more positive jumps than negative ones for this contract. The $BV_{1,t}$ version identifies 40 more jump days than the BV_t version of the test and 55 more jumps in total showing a significant difference in the detection capacity of the test after adjusting for market microstructure noise effects. The average absolute value of jumps is 0.200, which is similar to the EUR-USD futures, and positive and negative jumps have means of 0.203 and -0.197 respectively. Jumps range from -0.720 to 0.749, which are smaller measures of the extreme jumps than EUR-USD and represent the largest returns of the sample. The minimum values show that the returns identified as jumps are above 0.070 and below -0.075 showing that only large returns are identified as jumps. Average jump variation for individual intraday jumps is 0.045, which is similar to the daily jump variation of Table 4.4.4.2, but much smaller than the corresponding number for EUR-USD. Relative jump contributions are measured as 24.2% for individual jumps and 28.4% for daily jump variation, which are high contributions to realised variation although they are lower in magnitude than EUR-USD, and daily jump variation ranges from 15% to 80.4%. Decreasing α for a more stringent intraday jump test reduces the number of jumps discovered, but still identifies vastly more days containing jumps than the daily jump statistics. These fewer jumps are shown to be larger with higher means (in absolute terms) and this is confirmed by the minimum values that show that smaller jumps are no longer identified as jumps.

Standardisation of returns by average absolute returns in the second panel of Table 4.4.5.2 reveals 24 fewer days containing jumps and 28 fewer jumps in total. Lower minimum values show that, in addition to fewer jumps being identified, at least one large, negative return is identified as a jump compared to the raw returns, and this has the effect of reducing the mean size of intraday jumps. The elimination of some large jumps and the inclusion of smaller jumps reduce the measures of average jump variation and relative jump variation contribution to total variation. These statistics are also generally lower than those for EUR-USD. Standardisation of returns by the sample standard deviation of returns per five-minute interval further reduces the number of intraday jumps by 44 and the jumps are found to occur on 37 fewer days. The statistics are again very similar between the standardisation methods, but the fewer number of jumps identified in the bottom panel drives the means very slightly higher.

The statistics for JPY-USD in Table 4.4.5.3 are slightly lower than those for EUR-USD and higher than those for GBP-USD, despite evidence of far fewer jumps, specifically 465 jump days giving rise to 522 total intraday jumps. Again, there are more jump days identified than in the daily jump tests of section 4.4.4, and 13 more jump days and 33 more intraday jumps identified under the $BV_{I,t}$ than BV_t versions of the test. Average absolute jumps of 0.259 are remarkable with the higher number of positive jumps showing a slightly higher mean than negative jumps in absolute terms, measuring 0.264 and -0.247 respectively. The range of the jumps from -0.959 to 0.949 is wider than for GBP-USD, but the lower figure is not as low as for EUR-USD. Interestingly, these extreme jump values do not represent the largest absolute returns of the sample for JPY-USD, which measure 1.037 and -1.111 according to Table 4.4.3.1, meaning that these extreme returns are not identified as intraday jumps. Nevertheless, minimum values of 0.092 and -0.094 for positive and negative returns, respectively, confirm that only large returns are identified as intraday jumps. Jump variation (0.080) and relative jump contributions (26.6% and 29.8%) are also between those for GBP-USD and EUR-USD, which the maximum daily contribution to realised variation of 87.3% shows that the intraday jumps can be spectacular in both magnitude and contribution. Reducing the significance level of the test ensures that fewer intraday jumps are identified and these tend to show larger means, standard deviations and contributions to total variation indicating that a more stringent test correctly identifies fewer and larger high frequency returns as causing jumps.

Standardisation of returns by average absolute returns in the second panel of Table 4.4.5.3 reduces the number of jump days by 74 and the number of intraday jumps by 94. Average jump size falls and the standard deviation of the series increases showing higher dispersion around the mean. Equivalent maximum values and lower minimum values in absolute terms explain this reaction in the mean suggesting, that in addition to fewer intraday jumps detected, those that are identified include smaller jumps for standardised returns than the raw returns. The statistics in this second panel are similar to those for EUR-USD and are larger than those for GBP-USD. Finally, alternative standardisation by the return standard deviation causes a very slight further decrease in the numbers of intraday jumps detected. Such a slight fall in the detection implies that the standardisation underlying the statistics in the second and third panels of Table 4.4.5.3 are very similar to each other, being very similar to the corresponding statistics for EUR-USD and lower than those for GBP-USD.

The equity index futures markets shown in Tables 4.4.5.4 to 4.4.5.6 all show much fewer intraday jumps than the foreign exchange markets. The S&P 500 E-Mini contract in Table 4.4.5.4, for example, shows only 330 days containing jumps and 365 intraday jumps in total, however, this is far more than the corresponding 120, 158 and 218 daily jumps identified by the daily $Z_{1,t}$, $U_{1,t}$ and $W_{1,t}$ statistics of Table 4.4.4.4. There are more positive than negative jumps found and 2 fewer jump days and 11 fewer total intraday jumps identified by the $BV_{1,t}$ version of the test than the BV_t version. The S&P 500 E-Mini is the only market in the sample that shows a higher number of jumps when not adjusting for market microstructure noise effects. As noted in the previous section, this result may suggest that the staggering adjustment is unnecessary for this market and that market microstructure effects are mitigated by the selection of the five-minute sampling frequency.[24] The average absolute size of intraday jumps is 0.548, which shows that, although fewer jumps are detected in this market than the foreign exchange market, the jumps are far larger in size. Positive jumps show a mean of 0.538 and negative jumps show a mean of -0.560. Jumps range from -2.884 to 5.584, which shows just how extreme the largest

[24] Of course, this assertion requires more rigorous treatment to investigate the effects of market microstructure noise comprehensively, and this is left for future work.

jumps are, and these correspond to the largest five-minute returns of the S&P 500 E-Mini sample. The minimum of -2.884 is a staggering intraday jump, but is dwarfed by the incredible 5.584 maximum. The smallest jumps are measured as -0.144 and 0.154, which again show that only large returns are classified as jumps, and these lower limits are higher than those for the foreign exchange futures markets. Jump variation and relative jump contributions in the final three rows of the top panel are 0.486, 23.7% and 26.2% showing that jump variation is far higher in the S&P 500 E-Mini market than the foreign exchange markets yet contributes proportionately less to total variation on average. The maximum relative contribution of daily variation of 91.3% suggests, however, that jumps may explain the vast majority of realised variation on some days. Standard deviations are noticeably higher for the S&P 500 E-Mini market showing greater dispersion of the series around their means. Reducing the significance level of the test to 0.0001 again finds fewer jumps, which is entirely as expected, and the statistics suggest that the fewer intraday jumps that are detected are larger and contribute relatively more to total variation.

Results in the second panel of Table 4.4.5.4 show the intraday jumps summary statistics after standardising returns by the sample average absolute returns to annihilate the intraday volatility pattern. This standardisation reduces the number of jump days detected by 54 and the number of total intraday jumps by 66. There are still fewer jumps than for the foreign exchange futures markets, but far more than the daily jump test statistics displayed in Table 4.4.4.4. The results of these fewer jumps suggest lower average sizes of jumps and higher standard deviations caused by the inclusion of smaller jumps than is detected in raw returns. The statistics nevertheless remain far higher than the corresponding figures for the foreign exchange markets. Fewer and smaller jumps also have the effect of reducing the relative contributions of jumps to total variation, although the average jump variation increases following this standardisation. Standardisation by sample return standard deviation reduces the number of jump days detected by a further 24 days and the total number of intraday jumps detected by 26. This also causes a reduction in means, increases in standard deviations, and lower jump variations and relative contributions to total variation. The statistics remain far higher and approximately double those of the EUR-USD and JPY-USD markets, which in turn are larger than for the GBP-USD market.

The FTSE 100 market also shows fewer jump days (407) and fewer jumps (447) than the foreign exchange market as shown in Table 4.4.5.5, but there are more jumps identified than the S&P 500 E-Mini market. Confirming the pattern of all other markets, the FTSE 100 shows the presence of far more days containing jumps under the intraday jumps test than under the daily jump specification of section 4.4.4. Accounting for market microstructure noise finds 19 more jump days and 24 more intraday jumps than the standard procedure. Intraday jump size is 0.463 on average, which is much higher than for the foreign exchange futures, but is lower than the S&P 500 E-Mini. Positive and negative jumps have means of 0.453 and -0.473 respectively and intraday jump sizes range from -3.108 to 1.666, which represent the largest five-minute returns of either sign in the FTSE 100 futures sample. In contrast to the S&P 500 E-Mini market, the extreme negative jump is larger than the largest positive jump for the FTSE 100 and both extremes show the presence of very violent jumps. Jump variation averages 0.294, which is slightly lower than the average daily jump variation of Table 4.4.4.5 and the relative jump contributions have means of 20.6% for individual intraday jumps and 22.6% for daily jump contributions. These average relative contributions are lower than in both the S&P 500 E-Mini and the foreign exchange futures markets, although the range for the daily measure is from 9.6% to 83.1% showing that jumps are very important drivers of total variation on particular days. Intraday FTSE 100 futures jumps, therefore, are quite large but do not contribute as much towards total variation on average as in other markets. The effect of reducing the significance level of the test is to dramatically reduce the number of jumps detected, but retaining the larger jumps causing higher mean jump sizes, standard deviations and relative jump contributions.

The second panel of Table 4.4.5.5 repeats the test for returns standardised by sample average absolute returns. This results in a dramatic fall in the number of jumps detected, specifically the number of days containing jumps falls by 137 and the total number of intraday jumps identified drops by 137. The number of jumps identified remains below those for the foreign exchange market and, after this standardisation, is more comparable to the S&P 500 E-Mini market. Average sizes of jumps are lower after standardisation than for raw returns and this is likely caused by the inclusion of smaller intraday jumps. In comparison with other markets the statistics of this panel are smaller than those for the S&P 500 E-Mini and generally higher than those for the foreign exchange futures. The final panel of Table 4.4.5.5 tests for intraday jumps using returns standardised by sample return standard deviation. The effect of this is to reduce the number of jump days by a further 35 days and the total number of intraday jumps by 45, which represent further large reductions in numbers given the dramatic decrease mentioned above and witnessed in the second panel. This effect provides fewer intraday jumps than for the S&P 500 E-Mini and much less than the foreign exchange market. The fall in the average size of jumps and the increase in the minimum (absolute) jump values shows evidence that those fewer jumps that are detected include only the larger returns as jumps, and this helps to increase the contribution of jump variation to total variation.

To complete the analysis of the equity index markets, Table 4.4.5.6 shows the results of intraday jump tests for five-minute DJ Euro Stoxx 50 index futures raw and standardised returns. In the top panel, the test finds 415 days containing jumps and 463 total intraday jumps, which is fewer than in the foreign exchange markets but more than both the S&P 500 E-Mini and FTSE 100 futures contracts. These observations also illustrate more jump days than the daily jump test procedure displayed in Table 4.4.4.6, which finds 260, 269 and 341 daily jumps under $Z_{1,t}$, $U_{1,t}$ and $W_{1,t}$ specifications of the test respectively. Table 4.4.5.6 also reveals 1 more jump day and 7 more intraday jumps in total using the staggered $BV_{1,t}$ measure than the corresponding test performed using the standard BV_t measure. The DJ Euro Stoxx 50 futures market shows the highest average absolute jump size of all markets considered and the mean of 0.580 is double the highest average absolute jump of the foreign exchange market. Positive and negative jumps have respective means of 0.549 and -0.611 and jumps range from -5.541 to 2.034. In support of the figures for the FTSE 100 futures, the largest negative return dwarfs the largest positive return, and these extreme negative jumps correspond to the terrorist attacks on New York on 9th September 2001. Data for the S&P 500 E-Mini contract for this day was removed since the US markets closed shortly after the attacks. These extreme jumps correspond to the largest five-minute returns of the DJ Euro Stoxx 50 futures sample as displayed in Table 4.4.3.1. Minimum values of the jumps in absolute terms also show that only very large returns are classified as jumps. The average jump variation of individual intraday jumps is 0.501 and is very similar to the daily measure in Table 4.4.4.6, and is the highest measure of all foreign exchange and equity index futures markets. However, despite showing the largest average absolute jump size and jump variation, the average relative contribution of jumps to total variation is low compared to other markets, measuring 20.2% for individual intraday jumps and 22.5% for daily jump variation. The relative contribution of daily jump variation ranges from 10.4% to 86.1% showing that on some days jumps provide the majority of price variation. Standard deviations are noticeably high for the DJ Euro Stoxx 50 intraday jumps and this is in keeping with the other two equity index futures markets. Reducing the significance level of the test reduces the number of jumps detected and the larger jumps identified cause higher mean jump sizes and larger relative jump contributions to total variation.

The second panel of Table 4.4.5.6 shows the results of the intraday jump test performed on returns standardised by average absolute returns. As with all markets, this has the effect of reducing the number of jumps detected. This reduction is particularly dramatic for the DJ Euro Stoxx 50 futures market with the number of jump days falling by 154 between the first and second panels and the total number of jumps dropping by 170. The resultant number of jumps is comparable to the other equity index futures markets and is much lower than the foreign exchange markets. The standardisation also produces far more negative jumps (167) than positive jumps (126), whereas such asymmetry did not exist in raw returns. Mean jump sizes are lower since smaller returns are now identified as jumps, as shown by the lower minimum values of jumps in absolute terms, and these reduce the contribution of jump variation to total variation. Generally, the statistics are higher than those for foreign exchange markets, indicating larger jumps, and they are similar to the S&P 500 E-Mini futures and higher than the FTSE 100 contract. The final panel of the table repeats the analysis for returns standardised by the sample standard deviation of returns and this further reduces the presence of jumps, finding 17 fewer jump days and 24 fewer intraday jumps. These changes do not, however, have much effect on the descriptive statistics.

Turning to the interest rate futures markets, Table 4.4.5.7 shows the results of the intraday jump test for the US 10-Year Treasury Bond futures. This market shows many jumps, amounting to 513 jump days and a total of 596 intraday jumps, which are similar and slightly larger than the numbers of jumps found in the foreign exchange futures markets. There are many days exhibiting more than one jump and more negative jumps than positive jumps. In keeping with the results for the previous six markets, the intraday jump detection procedure finds far more days containing jumps than the daily jump detection method of section 4.4.4. There are also more jumps identified for the $BV_{1,t}$ version of the test than the standard BV_t version. The average absolute jump size of 0.225 is much smaller than that for the equity markets and is similar to the foreign exchange markets. Positive and negative jumps have similar means measuring 0.224 and -0.225 and jumps range from -1.457 to 0.954, which represent the largest returns of the US 10-Year T-Bond futures sample. These values are similar to the extreme returns in the foreign exchange market but are much lower than the corresponding maxima and minima for the equity index futures markets. Average jump variation of 0.071 for individual jumps is very similar to the daily jump variation measure of Table 4.4.4.7 and is lower than for equities, slightly lower than for EUR-USD and JPY-USD and higher than the GBP-USD market. Despite quite a low average jump variation, the contribution of this jump variation as a proportion of realised variation is the highest of all markets considered so far at an average of 30.7% for the individual intraday jump variation and 35.6% for the daily jump variation. Jumps in the US 10-Year T-Bond futures market, therefore, are not very large in comparison to the equity index futures markets, but contribute much more towards total variation on average. Reducing the significance level of the test again reduces the number of jumps detected, the effect of which is to include the larger jumps thus driving mean jump sizes and relative jump contributions higher.

Standardising raw returns by average absolute returns causes an enormous fall in the number of intraday jumps detected, the number of days showing at least one jump falls by 201 days and the total number of jumps found falls by 238. This fall is so dramatic that the resultant number of days containing jumps is lower than the daily jump test of section 4.4.4, and the US 10-Year T-Bond market is the only market in which this occurs. The implication of this is that larger returns are retained as intraday jumps, which increases average absolute jump size, minimum jump size (in absolute terms) and relative jump contribution. The statistics in this second panel of Table 4.4.5.7 are generally lower than those for equity index, EUR-USD and JPY-USD futures, and higher than GBP-USD futures, but the contribution of the jump variation to total variation is remarkably high. Adopting the sample standard deviation of returns as an alternative measure of the intraday volatility pattern causes yet further reduction in the number of intraday jumps identified, as shown by the third panel of Table 4.4.5.7. The number of days showing at least one jump drop by 33 and the total number of intraday jumps falls by 37, which makes the number of days containing at least one jump fall yet further below the corresponding number identified by the daily jump test procedure of Table 4.4.4.7. These fewer jump days cause a drop in the average absolute jump size between the second and third panels of the table and a corresponding drop in the relative contribution of jump variation.

Table 4.4.5.8 shows the summary statistics for the intraday jump test for the UK Gilt futures market. This shows an incredible 710 days containing at least one jump and a total of 880 intraday jumps. This is far more than any other market, far more jump days than the daily jump test suggests and is a surprisingly high number considering the use of a conservative significance level of 0.001. Most days provide only one intraday jump, but it is apparent from these numbers that some days will contain multiple jumps. There are more negative jumps than positive ones, more jumps detected for the $BV_{1,t}$ version than the BV_t version, and vastly more jumps detected than for the US 10-Year T-Bond market. The average absolute value of the jumps is 0.161, which is the smallest of all the markets considered so far and the jumps range from -0.788 to 0.618. Although these represent the largest five-minute returns of the Gilt sample, these are small compared to the other markets, and particularly the equity index markets. The minimum absolute jump is 0.052 showing that returns do not have to be as extreme in this market in order to be classed as intraday jumps. Average jump variation for individual jumps is also the lowest of all markets considered and the average relative jump contributions to total variation are also the smallest so far at 20% and 24.8% for individual and daily jump variation respectively. Changing the significance level of the test reduces the number of jumps detected by retaining the larger returns as jumps forcing the average jump size minimum absolute jump size and jump contribution upwards.

Standardising the raw returns by the average absolute returns causes large falls in the number of days containing jumps by 145 and the total number of jumps by 206. In addition to detecting fewer jumps, this standardisation includes lower returns as jumps compared to the raw returns and this causes the average jump size, minimum absolute jump size and jump contribution to drop to the lowest levels of all markets considered thus far. Standardisation of returns by sample return standard deviation per interval causes a further fall in the number of jump days identified by 25 days and the number of intraday jumps by 35. This does not, however, cause many changes to the summary statistics in the bottom panel of Table 4.4.5.8 and the averge jump sizes and contributions remain the smallest of all markets.

To complete the analysis of the interest rate futures markets, Table 4.4.5.9 displays the summary statistics for the intraday jump test performed on the Euro

Bund futures. The Bund futures provide 658 jump days for a total of 790 jumps, which are vast numbers of jumps for a sample of 2,022 days, but they are not quite as high as for the UK Gilt. Again, there are many days showing more than one jump, this technique discovers vastly more jumps than the daily jump detection method of section 4.4.4, and more jumps are detected under the BV_1 version of the test and there are many more negative jumps than positive jumps. The average absolute size of jumps is 0.146, which is the lowest of all nine futures markets. The jumps range between -0.613 and 0.574, which are the largest returns of the Bund sample, and this signifies that the largest price movements are not as large as the extreme movements of other markets, particularly the equity index markets. Jump variation (0.026) and relative jump contributions (19.9% and 23.9%) are also very low compared to the other markets. However, the relative daily jump variation contribution ranges from 9.2% to 90.9% implying that intraday jumps explain a staggering proportion of realised variation on some days and so, occasionally, jumps are critical factors in the underlying price process. Reducing the significance level of the test eliminates smaller jumps and increases average jump sizes and relative jump variation contributions. Standardising raw returns by average absolute returns reduces the number of jump days by 200 and cuts the total number of intraday jumps by 251, but this does not have much effect on the descriptive statistics. Adopting the standard deviation standardisation method in the third panel of Table 4.4.5.9 reduces the numbers of jumps further and this has very little effect on the descriptive statistics either.

To finalise this section, Figures 4.4.5.1 to 4.4.5.3 show the number of days containing different numbers of intraday jumps on the foreign exchange, equity index and interest rate futures markets respectively. The figures relate to the intraday jump test performed using the one-period staggered version of bipower variation in order to correct for market microstructure frictions. Each row of each figure represents a different market, whilst the three columns display the histograms for raw returns and returns standardised by average absolute returns and return standard deviation. Beginning with the foreign exchange markets, there is mostly one jump per day for each market, which confirms the evidence of Tables 4.4.5.1 to 4.4.5.3 above. Occasionally, there are two jumps per day and very rarely there are three. Fewer jumps are detected by a lower α and also after standardisation and these influences generate fewer days exhibiting multiple jumps.

Figure 4.4.5.1. Intraday Jumps per Day Using $BV_{1,t}$ for Foreign Exchange Futures.

EUR-USD

Raw Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	0	0
4	2	0	0
3	21	5	1
2	170	60	29
1	581	436	296

α

Returns Standardised by Average Absolute Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	2	0	0
3	16	4	0
2	98	44	24
1	551	362	224

α

Returns Standardised by Standard Deviation

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	3	0	0
3	9	2	0
2	105	41	18
1	534	351	216

α

GBP-USD

Raw Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	1	0	0
6	0	0	0
5	3	1	0
4	3	2	2
3	25	4	0
2	178	71	33
1	602	425	276

α

Returns Standardised by Average Absolute Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	1	1	0
5	1	0	0
4	7	1	1
3	28	9	5
2	153	59	27
1	602	409	258

α

Returns Standardised by Standard Deviation

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	1	0	0
5	1	1	0
4	5	1	1
3	34	9	5
2	139	53	28
1	603	378	228

α

JPY-USD

Raw Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	12	4	0
2	135	49	16
1	642	412	268

α

Returns Standardised by Average Absolute Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	11	1	0
2	102	35	11
1	583	355	208

α

Returns Standardised by Standard Deviation

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	12	1	0
2	102	38	12
1	574	346	209

α

Figure 4.4.5.2. Intraday Jumps per Day Using $BV_{1,t}$ for Equity Index Futures.

S&P 500 E-Mini

Raw Returns

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	1	0	0
3	12	2	0
2	84	31	7
1	489	297	176

Returns Standardised by Average Absolute Returns

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	6	0	0
2	78	23	7
1	417	253	173

Returns Standardised by Standard Deviation

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	4	0	0
2	72	21	4
1	395	231	151

FTSE 100

Raw Returns

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	11	0	0
2	116	40	13
1	570	367	238

Returns Standardised by Average Absolute Returns

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	1	0	0
3	10	0	0
2	70	30	11
1	414	240	134

Returns Standardised by Standard Deviation

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	1	0	0
3	11	2	0
2	56	16	8
1	389	217	117

DJ Euro Stoxx 50

Raw Returns

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	3	0	0
3	19	4	2
2	108	40	13
1	574	371	247

Returns Standardised by Average Absolute Returns

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	1	0	0
3	15	1	0
2	64	30	13
1	398	230	144

Returns Standardised by Standard Deviation

Intraday Jumps \ α	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	1	0	0
3	11	1	1
2	60	23	9
1	404	220	134

Figure 4.4.5.3. Intraday Jumps per Day Using $BV_{1,t}$ for Interest Rate Futures.

US 10-Year Treasury Bond

Raw Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	1	0	0
6	0	0	0
5	1	0	0
4	2	2	1
3	19	7	2
2	131	63	35
1	581	441	339

α

Returns Standardised by Average Absolute Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	2	0	0
4	1	1	1
3	9	6	5
2	83	31	17
1	423	274	182

α

Returns Standardised by Standard Deviation

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	2	0	0
4	1	1	1
3	9	6	4
2	81	27	14
1	384	245	169

α

UK Gilt

Raw Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	2	0	0
5	3	0	0
4	13	3	2
3	51	23	8
2	235	115	62
1	733	569	425

α

Returns Standardised by Average Absolute Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	1	0	0
5	4	1	1
4	9	3	0
3	31	10	5
2	175	76	37
1	685	475	327

α

Returns Standardised by Standard Deviation

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	1	0	0
5	3	1	1
4	7	1	0
3	34	10	4
2	156	72	33
1	681	456	307

α

Euro Bund

Raw Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	0	0
4	6	0	0
3	36	14	4
2	233	104	63
1	713	540	396

α

Returns Standardised by Average Absolute Returns

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	1	0
4	1	0	0
3	23	8	3
2	149	61	35
1	584	388	260

α

Returns Standardised by Standard Deviation

Intraday Jumps	0.01	0.001	0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	0	0
4	1	1	0
3	23	9	4
2	133	47	26
1	574	373	254

α

The GBP-USD is a more interesting case since it is rare for a day to contain more than two intraday jumps, and yet there are two days containing four intraday jumps and one day with five. Whilst these days would be very interesting case studies to investigate further, it is important to note that the evidence in Table 4.4.5.2 suggests that these jumps are likely to be particularly small in comparison with the EUR-USD and JPY-USD markets.

The equity index futures markets in Figure 4.4.5.2 is more straightforward showing at most three intraday jumps on any one day and this is a rare occurrence. A lower significance level for the test finds fewer jumps and fewer multiple jump days. Standardisation of returns also has the same effect, although using the standard deviation of returns in the standardisation finds more days containing three intraday jumps for the FTSE 100 market. The interest rate futures in Figure 4.4.5.3 confirm that the majority of jump days contain a single intraday jump. More intraday jumps are detected in total in these markets and so it is not surprising that there are many days containing two jumps. Consistent with the foreign exchange markets, some days contain three or possibly four intraday jumps, but these do not occur often. Standardisation of returns finds fewer intraday jumps and the evidence in Tables 4.4.5.1 to 4.4.5.9 suggest that those intraday jumps identified are smaller than for raw returns. The finding of days containing five jumps after standardisation for the UK Gilt and Euro Bund markets is likely to be explained by the presence of smaller jumps. The general effect of lowering the significance level of the test is to find fewer but larger jumps and this is confirmed in Figure 4.4.5.3 as fewer multiple jump days are found for lower α.

To conclude this section, the intraday jump detection technique of Andersen, Bollerslev and Dobrev (2007) finds far more days containing jumps than the daily jump detection method used in section 4.4.4. Jumps are large in the equity index futures markets and are smaller and more frequent in the foreign exchange futures markets. The largest jumps correspond to the largest returns of the sample of either sign, but this finding requires further investigation in order to assess whether all large returns are classified by this technique as intraday jumps. Jump variation can also contribute vast proportions of total daily price variation and this is easily seen by the maximum values that the relative jump contributions reach in each market. Jumps, therefore, are an important feature of the underlying price process and this method offers a way of pinpointing the exact timing of the jumps. This intraday jump detection technique relies on volatility being constant throughout the day. There is a wealth of empirical evidence to suggest that this is an inaccurate assumption and so this section has applied two alternative standardisation methods in order to nullify the ubiquitous intraday volatility pattern. The effect of these standardisations is to detect fewer intraday jumps. Whilst this method retains the very largest jumps, and with them the largest relative jump variation contributions, it also includes smaller returns that the method applied to raw returns did not detect as jumps. In order to assess whether the standardisation techniques identify intraday jumps more accurately, section 4.5 will compare the timings of these jumps in conjunction with the announcement of macroeconomic news as possible causes of these jumps. Finally, some days show the presence of multiple intraday jumps, particularly for the foreign exchange and interest rate futures markets, and this is also more common after standardising returns by the intraday volatility pattern, which may imply that some smaller intraday jumps are detected on days that already contain multiple jumps that were not identified by the raw returns. The following section therefore investigates an alternative method for identifying intraday jumps.

4.4.6 Sequential Intraday Jumps

The sequential method for identifying intraday jumps has been proposed by Andersen, Bollerslev, Frederiksen and Nielsen (2006). The non-parametric methodology of section 4.3.5 explains that, assuming only a single jump on a particular day, the contribution to total volatility arising from the jump is estimated by:

$$\widetilde{JV}_{t,k} = I[W_{t+1} > \Phi_{1-\alpha}] \cdot \left(\max r^2_{t+j\cdot\Delta,\Delta} - \frac{\Delta}{1-\Delta} \sum_{j=1, j\neq k}^{1/\Delta} r^2_{t+j\cdot\Delta,\Delta} \right), \tag{4.37a}$$

$$\widetilde{JV}_{t,k} = I[Z_{t+1} > \Phi_{1-\alpha}] \cdot \left(\max r^2_{t+j\cdot\Delta,\Delta} - \frac{\Delta}{1-\Delta} \sum_{j=1, j\neq k}^{1/\Delta} r^2_{t+j\cdot\Delta,\Delta} \right), \tag{4.37b}$$

$$\widetilde{JV}_{t,k} = I[U_{t+1} > \Phi_{1-\alpha}] \cdot \left(\max r^2_{t+j\cdot\Delta,\Delta} - \frac{\Delta}{1-\Delta} \sum_{j=1, j\neq k}^{1/\Delta} r^2_{t+j\cdot\Delta,\Delta} \right), \tag{4.37c}$$

where $I[\cdot]$ is an indicator function and k denotes the precise intraday interval containing the jump. The corresponding return during interval k indicates the direction of the jump and measures its magnitude:

$$\widetilde{\kappa}_k = r_{t+k\cdot\Delta,\Delta}\,. \tag{4.38}$$

The sequential detection of numerous jumps during a particular day occurs as follows. First, the realised variation, RV_{t+1}, is calculated as the summation of all the squared intraday returns according to equation (4.2). If the daily jump test, W_{t+1}, Z_{t+1} or U_{t+1} rejects the null hypothesis that there are no jumps, at least one jump is identified during this day and the contribution of the jump to total daily variation is measured as the difference between the largest squared intraday return and the average of the remaining $(1/\Delta - 1)$ squared returns. To identify a second possible jump, Andersen, Bollerslev, Frederiksen and Nielsen (2006) correct RV_{t+1} for the first jump by re-calculating it as the summation of squared intraday returns where the squared return containing the first jump is replaced by the average of the remaining $(1/\Delta - 1)$ squared returns, which exclude this first jump. The daily jump test statistic, W_{t+1}, Z_{t+1} or U_{t+1}, is re-calculated by replacing RV_{t+1} with the corresponding jump-adjusted realised variation measure. If this second test does not reject the null, there is evidence of exactly one jump on this particular day and the sequential procedure is stopped. If the second test rejects again, there are at least two jumps, and the contribution of the second jump is calculated as the second largest squared return less the average of the remaining $(1/\Delta - 2)$ squared returns, which exclude both intraday jumps. Realised volatility for this day is then adjusted for the second jump, by replacing the second largest squared return with the average of the remaining squared returns and the sequence continues until the corresponding daily jump test no longer rejects the null. This sequential method is employed in this chapter by replacing standard measures of realised bipower variation and tripower quarticity with their staggered counterparts in order to annihilate the effects of market microstructure noise.

Tables 4.4.6.1 to 4.4.6.9 show the summary statistics for the intraday jump series detected using the sequential method of Andersen, Bollerslev, Frederiksen and

Nielsen (2006) across various significance levels for the daily jump test and across various daily jump test statistics. The tables follow the same pattern as those in section 4.4.5 and the variable $J\widetilde{V}D_t$ measures the daily jump contribution by summing all intraday jump contributions over each day. From the construction of the test, the number of days showing at least one jump is always identical to the number of daily jump days identified in Tables 4.4.4.1 to 4.4.4.9 and, following the approach adopted in describing the evidence presented in those tables, the analysis here similarly focuses on a significance level of 0.001 and the test statistic Z_I as the preferred test specification.

For EUR-USD in Table 4.4.6.1, there are 222 days containing at least one jump and 239 intraday jumps in total under the $Z_{I,t}$ specification of the daily jump test and a significance level of 0.001. It is obvious therefore that some days contain more than one jump. The mean absolute size of the jumps is 0.270, which is very similar to Table 4.4.5.1 of the previous section for 332 fewer intraday jumps. The reduction in the number of jumps identified is a consistent result throughout this section, showing that the sequential method is more stringent and detects far fewer intraday jumps than in section 4.4.5 suggesting that large individual returns do not always do not always constitiute a jump relative to daily variation measures. Intraday jumps range from -1.379 to 0.948, precisely as before and corresponding to the largest returns of the EUR-USD sample. Average jump variation and relative jump contribution (0.100 and 28.0% respectively) are both higher than in Table 4.4.5.1, but the mean relative contribution of daily jump variation at 30.1% is lower. This measure ranges up to 84.4%, which is not as high as for the jumps identified under the previous Andersen, Bollerslev and Dobrev (2007) method. Reducing the significance level of the test finds fewer jumps and retains the larger ones, thereby increasing the mean jump sizes, minimum absolute jump size and contribution. The $W_{I,t}$ and $U_{I,t}$ specifications find more jumps than the $Z_{I,t}$ version, as expected from the evidence presented in Table 4.4.4.1, however, the mean jump sizes and jump variation contributions are lower as compared to the $Z_{I,t}$ results. Finally, although not reported in full, the results for the BV_t version of the sequential test shows fewer jumps detected than under the $BV_{I,t}$ version, as expected from the evidence of section 4.4.4.

Table 4.4.6.1. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for EUR-USD Futures.

$W_{1,t}$												
A	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	597	293	304	514	363	175	188	323	263	128	135	239
	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.016	1.379	0.000	0.001	0.014	1.379	0.000	0.000	0.013	1.379	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.214	0.131	1.379	0.043	0.240	0.150	1.379	0.051	0.255	0.162	1.379	0.051
$\tilde{\kappa}_t^+$	0.214	0.137	0.948	0.043	0.246	0.159	0.948	0.051	0.262	0.170	0.948	0.051
$\tilde{\kappa}_t^-$	-0.215	0.126	-0.052	-1.379	-0.234	0.142	-0.052	-1.379	-0.248	0.155	-0.052	-1.379
$J\tilde{V}^*_{t,\Delta}$	0.061	0.116	1.895	0.002	0.078	0.143	1.895	0.002	0.089	0.162	1.895	0.002
$J\tilde{V}^*_{t,\Delta}/RV_t$	0.212	0.126	0.844	0.045	0.241	0.140	0.844	0.058	0.258	0.147	0.844	0.061
$J\tilde{V}D^*_t/RV_t$	0.246	0.131	0.844	0.060	0.271	0.141	0.844	0.061	0.284	0.147	0.844	0.077

$Z_{1,t}$												
A	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	476	231	245	418	239	119	120	222	126	59	67	120
	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.015	1.379	0.000	0.000	0.013	1.379	0.000	0.000	0.011	1.379	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.228	0.139	1.379	0.043	0.270	0.170	1.379	0.051	0.310	0.198	1.379	0.052
$\tilde{\kappa}_t^+$	0.231	0.147	0.948	0.043	0.279	0.179	0.948	0.051	0.326	0.204	0.948	0.075
$\tilde{\kappa}_t^-$	-0.225	0.132	-0.052	-1.379	-0.261	0.162	-0.052	-1.379	-0.295	0.194	-0.052	-1.379
$J\tilde{V}^*_{t,\Delta}$	0.069	0.128	1.895	0.002	0.100	0.171	1.895	0.002	0.133	0.217	1.895	0.002
$J\tilde{V}^*_{t,\Delta}/RV_t$	0.230	0.134	0.844	0.058	0.280	0.151	0.844	0.061	0.331	0.167	0.844	0.061
$J\tilde{V}D^*_t/RV_t$	0.262	0.136	0.844	0.061	0.301	0.147	0.844	0.091	0.347	0.163	0.844	0.061

$U_{1,t}$												
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	503	246	257	439	281	138	143	251	177	86	91	164
	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN	MEAN	SD	MAX	MIN
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.015	1.379	0.000	0.000	0.013	1.379	0.000	0.000	0.011	1.379	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.222	0.137	1.379	0.043	0.251	0.159	1.379	0.051	0.272	0.178	1.379	0.051
$\tilde{\kappa}_t^+$	0.223	0.143	0.948	0.043	0.257	0.166	0.948	0.051	0.285	0.183	0.948	0.051
$\tilde{\kappa}_t^-$	-0.221	0.132	-0.052	-1.379	-0.244	0.152	-0.052	-1.379	-0.259	0.173	-0.052	-1.379
$J\tilde{V}^*_{t,\Delta}$	0.066	0.124	1.895	0.002	0.086	0.158	1.895	0.002	0.103	0.187	1.895	0.002
$J\tilde{V}^*_{t,\Delta}/RV_t$	0.220	0.130	0.844	0.045	0.252	0.146	0.844	0.061	0.283	0.157	0.844	0.061
$J\tilde{V}D^*_t/RV_t$	0.252	0.133	0.844	0.060	0.282	0.147	0.844	0.077	0.306	0.156	0.844	0.061

Table 4.4.6.2. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for GBP-USD Futures.

$W_{1,t}$												
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	1,036	533	503	720	702	362	340	507	525	272	253	392
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.013	0.720	0.000	0.001	0.012	0.720	0.000	0.001	0.010	0.720	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.148	0.071	0.720	0.051	0.156	0.078	0.720	0.051	0.159	0.084	0.720	0.051
$\tilde{\kappa}_t^+$	0.150	0.074	0.683	0.051	0.158	0.082	0.683	0.051	0.163	0.090	0.683	0.051
$\tilde{\kappa}_t^-$	-0.146	0.068	-0.051	-0.720	-0.154	0.074	-0.051	-0.720	-0.156	0.077	-0.051	-0.720
$J\tilde{V}_{t,k}^*$	0.026	0.037	0.515	0.002	0.029	0.044	0.515	0.002	0.031	0.049	0.515	0.002
$J\tilde{V}_{t,k}^*/RV_t$	0.160	0.096	0.763	0.024	0.173	0.106	0.763	0.024	0.183	0.115	0.763	0.024
$J\tilde{V}D_t^*/RV_t$	0.230	0.114	0.763	0.060	0.240	0.118	0.763	0.064	0.245	0.123	0.763	0.048

$Z_{1,t}$												
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	861	439	422	615	481	253	228	364	286	150	136	228
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.013	0.720	0.000	0.001	0.010	0.720	0.000	0.000	0.009	0.720	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.153	0.076	0.720	0.051	0.162	0.086	0.720	0.051	0.175	0.098	0.720	0.051
$\tilde{\kappa}_t^+$	0.155	0.081	0.683	0.051	0.164	0.092	0.683	0.051	0.177	0.105	0.683	0.051
$\tilde{\kappa}_t^-$	-0.151	0.070	-0.051	-0.720	-0.160	0.079	-0.051	-0.720	-0.173	0.088	-0.056	-0.720
$J\tilde{V}_{t,k}^*$	0.028	0.041	0.515	0.002	0.032	0.051	0.515	0.002	0.039	0.061	0.515	0.002
$J\tilde{V}_{t,k}^*/RV_t$	0.169	0.103	0.763	0.024	0.189	0.117	0.763	0.024	0.211	0.131	0.763	0.024
$J\tilde{V}D_t^*/RV_t$	0.236	0.118	0.763	0.064	0.250	0.126	0.763	0.065	0.264	0.137	0.763	0.067

$U_{1,t}$												
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	883	450	433	629	543	279	264	403	380	196	184	293
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.013	0.720	0.000	0.001	0.011	0.720	0.000	0.000	0.009	0.720	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.151	0.073	0.720	0.051	0.159	0.083	0.720	0.051	0.167	0.092	0.720	0.051
$\tilde{\kappa}_t^+$	0.154	0.077	0.683	0.051	0.162	0.089	0.683	0.051	0.172	0.099	0.683	0.051
$\tilde{\kappa}_t^-$	-0.149	0.070	-0.051	-0.720	-0.156	0.076	-0.051	-0.720	-0.162	0.083	-0.051	-0.720
$J\tilde{V}_{t,k}^*$	0.027	0.040	0.515	0.002	0.031	0.048	0.515	0.002	0.035	0.056	0.515	0.002
$J\tilde{V}_{t,k}^*/RV_t$	0.165	0.100	0.763	0.024	0.182	0.114	0.763	0.024	0.197	0.123	0.763	0.024
$J\tilde{V}D_t^*/RV_t$	0.232	0.115	0.763	0.060	0.245	0.123	0.763	0.048	0.255	0.128	0.763	0.068

Table 4.4.6.3. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for JPY-USD Futures.

$W_{1,t}$												
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	673	361	312	563	414	219	195	372	311	165	146	287
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.015	0.989	0.000	0.001	0.013	0.989	0.000	0.000	0.012	0.989	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.193	0.124	0.989	0.043	0.214	0.142	0.989	0.043	0.223	0.148	0.989	0.043
$\tilde{\kappa}_t^+$	0.200	0.125	0.949	0.043	0.223	0.145	0.949	0.043	0.229	0.145	0.889	0.043
$\tilde{\kappa}_t^-$	-0.186	0.122	-0.057	-0.989	-0.204	0.139	-0.059	-0.989	-0.215	0.151	-0.071	-0.989
$J\tilde{V}_{t,k}^*$	0.051	0.096	0.973	0.002	0.064	0.118	0.973	0.002	0.069	0.125	0.973	0.002
$J\tilde{V}_{t,k}^*/RV_t$	0.192	0.121	0.783	0.044	0.216	0.134	0.783	0.051	0.232	0.142	0.783	0.051
$J\tilde{V}D_t^*/RV_t$	0.229	0.127	0.873	0.068	0.241	0.137	0.873	0.067	0.251	0.146	0.873	0.059

$Z_{1,t}$												
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	513	275	238	452	253	136	117	234	121	67	54	117
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.014	0.989	0.000	0.000	0.012	0.989	0.000	0.000	0.010	0.989	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.210	0.137	0.989	0.043	0.244	0.166	0.989	0.043	0.294	0.190	0.989	0.064
$\tilde{\kappa}_t^+$	0.217	0.140	0.949	0.043	0.250	0.168	0.949	0.043	0.300	0.185	0.889	0.064
$\tilde{\kappa}_t^-$	-0.202	0.134	-0.059	-0.989	-0.237	0.164	-0.071	-0.989	-0.287	0.198	-0.071	-0.989
$J\tilde{V}_{t,k}^*$	0.061	0.110	0.973	0.002	0.085	0.145	0.973	0.002	0.120	0.177	0.973	0.004
$J\tilde{V}_{t,k}^*/RV_t$	0.211	0.131	0.783	0.051	0.256	0.153	0.783	0.059	0.322	0.170	0.783	0.072
$J\tilde{V}D_t^*/RV_t$	0.239	0.135	0.873	0.067	0.276	0.158	0.873	0.059	0.333	0.179	0.873	0.080

$U_{1,t}$												
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	556	296	260	477	328	175	153	298	196	112	84	183
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.014	0.989	0.000	0.000	0.012	0.989	0.000	0.000	0.011	0.989	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.201	0.131	0.989	0.043	0.219	0.146	0.989	0.043	0.247	0.171	0.989	0.064
$\tilde{\kappa}_t^+$	0.208	0.132	0.949	0.043	0.224	0.143	0.889	0.043	0.246	0.164	0.889	0.064
$\tilde{\kappa}_t^-$	-0.192	0.130	-0.058	-0.989	-0.213	0.150	-0.071	-0.989	-0.248	0.181	-0.071	-0.989
$J\tilde{V}_{t,k}^*$	0.055	0.105	0.973	0.002	0.067	0.122	0.973	0.002	0.088	0.151	0.973	0.004
$J\tilde{V}_{t,k}^*/RV_t$	0.201	0.126	0.783	0.044	0.227	0.141	0.783	0.051	0.260	0.162	0.783	0.051
$J\tilde{V}D_t^*/RV_t$	0.234	0.130	0.873	0.068	0.250	0.145	0.873	0.059	0.279	0.164	0.873	0.064

Table 4.4.6.4. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for S&P 500 E-Mini Futures.

	$W_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	399	213	186	352	234	119	115	218	147	81	66	135
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.028	5.584	0.000	0.001	0.026	5.584	0.000	0.000	0.024	5.584	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.425	0.438	5.584	0.094	0.499	0.536	5.584	0.094	0.570	0.650	5.584	0.105
$\tilde{\kappa}_t^+$	0.408	0.483	5.584	0.094	0.499	0.614	5.584	0.094	0.565	0.725	5.584	0.105
$\tilde{\kappa}_t^-$	-0.444	0.381	-0.113	-2.884	-0.499	0.444	-0.122	-2.884	-0.576	0.548	-0.122	-2.884
$J\tilde{V}_{i,t}^*$	0.363	1.729	31.061	0.008	0.526	2.239	31.061	0.008	0.734	2.804	31.061	0.010
$J\tilde{V}_{i,t}^*/RV_t$	0.177	0.119	0.863	0.047	0.208	0.137	0.863	0.051	0.234	0.158	0.863	0.051
$J\tilde{V}D_t^*/RV_t$	0.200	0.124	0.925	0.047	0.223	0.141	0.925	0.062	0.254	0.163	0.925	0.051

	$Z_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	318	163	155	294	129	65	64	120	57	29	28	56
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.027	5.584	0.000	0.000	0.024	5.584	0.000	0.000	0.022	5.584	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.464	0.479	5.584	0.094	0.621	0.681	5.584	0.122	0.892	0.919	5.584	0.154
$\tilde{\kappa}_t^+$	0.458	0.540	5.584	0.094	0.634	0.793	5.584	0.124	0.915	1.108	5.584	0.154
$\tilde{\kappa}_t^-$	-0.470	0.407	-0.113	-2.884	-0.608	0.550	-0.122	-2.884	-0.867	0.690	-0.166	-2.884
$J\tilde{V}_{i,t}^*$	0.435	1.931	31.061	0.008	0.835	2.982	31.061	0.012	1.611	4.371	31.061	0.022
$J\tilde{V}_{i,t}^*/RV_t$	0.195	0.127	0.863	0.051	0.254	0.162	0.863	0.051	0.345	0.186	0.863	0.098
$J\tilde{V}D_t^*/RV_t$	0.211	0.131	0.925	0.062	0.273	0.166	0.925	0.051	0.351	0.195	0.925	0.098

	$U_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	341	179	162	309	171	91	80	158	88	45	43	82
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.027	5.584	0.000	0.000	0.024	5.584	0.000	0.000	0.022	5.584	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.444	0.465	5.584	0.094	0.542	0.600	5.584	0.105	0.687	0.777	5.584	0.154
$\tilde{\kappa}_t^+$	0.431	0.520	5.584	0.094	0.526	0.673	5.584	0.105	0.701	0.910	5.584	0.154
$\tilde{\kappa}_t^-$	-0.458	0.397	-0.113	-2.884	-0.561	0.508	-0.122	-2.884	-0.672	0.620	-0.159	-2.884
$J\tilde{V}_{i,t}^*$	0.404	1.866	31.061	0.008	0.642	2.596	31.061	0.010	1.059	3.568	31.061	0.022
$J\tilde{V}_{i,t}^*/RV_t$	0.185	0.123	0.863	0.047	0.224	0.150	0.863	0.051	0.279	0.176	0.863	0.072
$J\tilde{V}D_t^*/RV_t$	0.204	0.127	0.925	0.047	0.243	0.155	0.925	0.051	0.299	0.181	0.925	0.072

Table 4.4.6.5. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for FTSE 100 Futures.

	$W_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	529	269	260	450	312	166	146	285	199	107	92	187
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.021	1.799	0.000	0.001	0.018	1.799	0.000	0.000	0.015	1.799	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.352	0.239	1.799	0.089	0.385	0.268	1.799	0.095	0.412	0.298	1.799	0.102
$\tilde{\kappa}_t^+$	0.354	0.236	1.649	0.089	0.381	0.256	1.649	0.102	0.414	0.282	1.649	0.102
$\tilde{\kappa}_t^-$	-0.351	0.242	-0.095	-1.799	-0.390	0.282	-0.095	-1.799	-0.410	0.317	-0.106	-1.799
$J\tilde{V}_{t,k}^*$	0.174	0.315	3.216	0.007	0.213	0.382	3.216	0.008	0.251	0.455	3.216	0.010
$J\tilde{V}_{t,k}^*/RV_t$	0.152	0.093	0.671	0.042	0.175	0.105	0.671	0.052	0.195	0.114	0.671	0.055
$J\tilde{V}D_t^*/RV_t$	0.179	0.097	0.671	0.051	0.192	0.106	0.671	0.052	0.208	0.113	0.671	0.055

	$Z_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	426	218	208	380	193	102	91	183	97	51	46	93
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.019	1.799	0.000	0.000	0.016	1.799	0.000	0.000	0.013	1.799	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.369	0.250	1.799	0.089	0.440	0.306	1.799	0.095	0.506	0.362	1.799	0.113
$\tilde{\kappa}_t^+$	0.366	0.246	1.649	0.089	0.429	0.288	1.649	0.122	0.507	0.343	1.649	0.123
$\tilde{\kappa}_t^-$	-0.372	0.256	-0.095	-1.799	-0.453	0.326	-0.095	-1.799	-0.506	0.387	-0.113	-1.799
$J\tilde{V}_{t,k}^*$	0.192	0.343	3.216	0.007	0.279	0.466	3.216	0.008	0.379	0.607	3.216	0.012
$J\tilde{V}_{t,k}^*/RV_t$	0.164	0.098	0.671	0.042	0.211	0.116	0.671	0.056	0.249	0.130	0.671	0.078
$J\tilde{V}D_t^*/RV_t$	0.184	0.102	0.671	0.055	0.222	0.115	0.671	0.067	0.260	0.127	0.671	0.078

	$U_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	456	234	222	395	226	121	105	209	128	69	59	120
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.020	1.799	0.000	0.000	0.016	1.799	0.000	0.000	0.013	1.799	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.362	0.246	1.799	0.089	0.399	0.287	1.799	0.102	0.455	0.332	1.799	0.106
$\tilde{\kappa}_t^+$	0.358	0.241	1.649	0.089	0.400	0.272	1.649	0.102	0.454	0.311	1.649	0.123
$\tilde{\kappa}_t^-$	-0.365	0.251	-0.095	-1.799	-0.397	0.304	-0.106	-1.799	-0.457	0.357	-0.106	-1.799
$J\tilde{V}_{t,k}^*$	0.184	0.334	3.216	0.007	0.234	0.431	3.216	0.010	0.309	0.539	3.216	0.010
$J\tilde{V}_{t,k}^*/RV_t$	0.157	0.096	0.671	0.042	0.186	0.111	0.671	0.055	0.219	0.124	0.671	0.060
$J\tilde{V}D_t^*/RV_t$	0.181	0.100	0.671	0.052	0.201	0.111	0.671	0.055	0.234	0.121	0.671	0.067

Table 4.4.6.6. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for DJ Euro Stoxx 50 Futures.

$W_{1,t}$

α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$
	700	358	342	531	415	216	199	341	289	158	131	238
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.030	5.541	0.000	0.001	0.022	2.034	0.000	0.001	0.020	2.034	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.384	0.363	5.541	0.098	0.400	0.318	2.034	0.099	0.424	0.346	2.034	0.099
$\tilde{\kappa}_t^+$	0.362	0.292	2.034	0.099	0.392	0.325	2.034	0.099	0.415	0.363	2.034	0.099
$\tilde{\kappa}_t^-$	-0.408	0.424	-0.098	-5.541	-0.408	0.311	-0.099	-1.989	-0.434	0.326	-0.099	-1.601
$\tilde{JV}_{t,k}^*$	0.270	1.260	30.352	0.008	0.252	0.496	3.993	0.009	0.291	0.542	3.993	0.009
$\tilde{JV}_{t,k}^*/RV_t$	0.133	0.097	0.861	0.023	0.153	0.110	0.861	0.034	0.168	0.124	0.861	0.036
$\tilde{JVD}_t^*/RV_t$	0.176	0.105	0.861	0.035	0.187	0.111	0.861	0.051	0.204	0.123	0.861	0.048

$Z_{1,t}$

α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$
	618	315	303	477	310	172	138	260	157	90	67	143
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.029	5.541	0.000	0.001	0.024	5.541	0.000	0.000	0.018	2.745	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.395	0.387	5.541	0.098	0.439	0.468	5.541	0.099	0.515	0.447	2.745	0.099
$\tilde{\kappa}_t^+$	0.375	0.317	2.034	0.099	0.399	0.356	2.034	0.099	0.480	0.430	2.034	0.099
$\tilde{\kappa}_t^-$	-0.417	0.448	-0.098	-5.541	-0.489	0.575	-0.099	-5.541	-0.563	0.469	-0.111	-2.745
$\tilde{JV}_{t,k}^*$	0.296	1.344	30.352	0.008	0.401	1.833	30.352	0.009	0.454	0.878	7.473	0.009
$\tilde{JV}_{t,k}^*/RV_t$	0.140	0.102	0.861	0.034	0.167	0.123	0.861	0.036	0.206	0.147	0.861	0.045
$\tilde{JVD}_t^*/RV_t$	0.181	0.107	0.861	0.035	0.199	0.123	0.861	0.048	0.226	0.146	0.861	0.045

$U_{1,t}$

α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(\tilde{JVD}^*)$
	604	310	294	466	323	178	145	269	196	116	80	167
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.026	2.745	0.000	0.001	0.020	2.034	0.000	0.000	0.018	2.034	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.382	0.314	2.745	0.098	0.415	0.334	2.034	0.099	0.461	0.390	2.034	0.099
$\tilde{\kappa}_t^+$	0.367	0.293	2.034	0.099	0.410	0.348	2.034	0.099	0.432	0.394	2.034	0.099
$\tilde{\kappa}_t^-$	-0.399	0.334	-0.098	-2.745	-0.421	0.316	-0.099	-1.601	-0.503	0.381	-0.099	-1.601
$\tilde{JV}_{t,k}^*$	0.235	0.556	7.473	0.008	0.275	0.517	3.993	0.009	0.354	0.629	3.993	0.009
$\tilde{JV}_{t,k}^*/RV_t$	0.137	0.100	0.861	0.023	0.163	0.119	0.861	0.036	0.182	0.135	0.861	0.045
$\tilde{JVD}_t^*/RV_t$	0.178	0.107	0.861	0.042	0.196	0.119	0.861	0.048	0.214	0.134	0.861	0.057

Table 4.4.6.7. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for US 10-Year Treasury Bond Futures.

	$W_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	1,010	484	526	653	676	329	347	453	507	238	269	358
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.015	1.457	0.000	0.001	0.014	1.457	0.000	0.001	0.013	1.457	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.134	0.134	1.457	0.026	0.149	0.150	1.457	0.026	0.160	0.160	1.457	0.026
$\tilde{\kappa}_t^+$	0.135	0.129	0.954	0.026	0.151	0.148	0.954	0.026	0.164	0.156	0.954	0.027
$\tilde{\kappa}_t^-$	-0.134	0.138	-0.026	-1.457	-0.147	0.153	-0.026	-1.457	-0.156	0.164	-0.026	-1.457
$J\tilde{V}_{t,k}^*$	0.035	0.111	2.113	0.000	0.044	0.132	2.113	0.000	0.050	0.145	2.113	0.000
$J\tilde{V}_{t,k}^*/RV_t$	0.178	0.165	0.885	0.010	0.206	0.184	0.885	0.010	0.225	0.195	0.885	0.012
$J\tilde{V}D_t^*/RV_t$	0.276	0.168	0.885	0.042	0.307	0.176	0.885	0.040	0.318	0.186	0.885	0.042

	$Z_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	879	431	448	563	517	243	274	354	312	139	173	228
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.015	1.457	0.000	0.001	0.014	1.457	0.000	0.000	0.012	1.457	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.141	0.142	1.457	0.026	0.164	0.167	1.457	0.026	0.182	0.189	1.457	0.027
$\tilde{\kappa}_t^+$	0.140	0.136	0.954	0.026	0.169	0.166	0.954	0.027	0.187	0.186	0.954	0.027
$\tilde{\kappa}_t^-$	-0.142	0.148	-0.026	-1.457	-0.159	0.168	-0.026	-1.457	-0.179	0.191	-0.027	-1.457
$J\tilde{V}_{t,k}^*$	0.039	0.119	2.113	0.000	0.054	0.150	2.113	0.000	0.068	0.180	2.113	0.000
$J\tilde{V}_{t,k}^*/RV_t$	0.190	0.175	0.885	0.010	0.226	0.200	0.885	0.012	0.259	0.223	0.885	0.012
$J\tilde{V}D_t^*/RV_t$	0.297	0.170	0.885	0.040	0.330	0.187	0.885	0.042	0.355	0.206	0.885	0.061

	$U_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	868	426	442	562	528	249	279	373	364	165	199	273
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.015	1.457	0.000	0.001	0.013	1.457	0.000	0.000	0.012	1.457	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.140	0.141	1.457	0.026	0.158	0.157	1.457	0.026	0.175	0.176	1.457	0.027
$\tilde{\kappa}_t^+$	0.138	0.135	0.954	0.026	0.162	0.153	0.954	0.027	0.182	0.170	0.954	0.027
$\tilde{\kappa}_t^-$	-0.142	0.147	-0.026	-1.457	-0.154	0.162	-0.026	-1.457	-0.169	0.181	-0.027	-1.457
$J\tilde{V}_{t,k}^*$	0.039	0.119	2.113	0.000	0.049	0.143	2.113	0.000	0.061	0.168	2.113	0.000
$J\tilde{V}_{t,k}^*/RV_t$	0.188	0.173	0.885	0.010	0.222	0.192	0.885	0.012	0.251	0.207	0.885	0.017
$J\tilde{V}D_t^*/RV_t$	0.291	0.171	0.885	0.050	0.314	0.184	0.885	0.042	0.334	0.196	0.885	0.057

Table 4.4.6.8. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for UK Gilt Futures.

	$W_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	1,119	528	591	819	736	363	373	578	516	251	265	416
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.010	0.788	0.000	0.000	0.009	0.788	0.000	0.000	0.008	0.788	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.125	0.081	0.788	0.028	0.136	0.091	0.788	0.028	0.145	0.099	0.788	0.029
$\tilde{\kappa}_t^+$	0.125	0.076	0.526	0.029	0.136	0.084	0.526	0.029	0.145	0.090	0.526	0.029
$\tilde{\kappa}_t^-$	-0.125	0.085	-0.028	-0.788	-0.136	0.098	-0.028	-0.788	-0.144	0.108	-0.037	-0.788
$J\tilde{V}_{t,k}^*$	0.021	0.042	0.605	0.001	0.026	0.050	0.605	0.001	0.030	0.056	0.605	0.001
$J\tilde{V}_{t,k}^*/RV_t$	0.149	0.104	0.744	0.018	0.167	0.117	0.744	0.018	0.180	0.125	0.744	0.028
$J\tilde{V}D_t^*/RV_t$	0.203	0.120	0.774	0.041	0.213	0.131	0.774	0.049	0.223	0.139	0.774	0.045

	$Z_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	997	475	522	752	560	281	279	462	320	162	158	268
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.010	0.788	0.000	0.000	0.009	0.788	0.000	0.000	0.007	0.788	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.130	0.084	0.788	0.028	0.146	0.097	0.788	0.029	0.168	0.109	0.788	0.037
$\tilde{\kappa}_t^+$	0.130	0.079	0.526	0.029	0.146	0.090	0.526	0.029	0.169	0.105	0.526	0.050
$\tilde{\kappa}_t^-$	-0.130	0.088	-0.028	-0.788	-0.146	0.103	-0.037	-0.788	-0.167	0.114	-0.037	-0.788
$J\tilde{V}_{t,k}^*$	0.023	0.044	0.605	0.001	0.030	0.054	0.605	0.001	0.039	0.061	0.605	0.001
$J\tilde{V}_{t,k}^*/RV_t$	0.156	0.108	0.744	0.018	0.188	0.125	0.744	0.028	0.222	0.142	0.744	0.033
$J\tilde{V}D_t^*/RV_t$	0.207	0.124	0.774	0.049	0.228	0.138	0.774	0.045	0.265	0.150	0.774	0.056

	$U_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\lvert\tilde{\kappa}_t\rvert^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	982	469	513	739	589	288	301	474	373	184	189	305
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\lvert\tilde{\kappa}_t\rvert$	0.001	0.010	0.788	0.000	0.000	0.008	0.788	0.000	0.000	0.007	0.788	0.000
$\lvert\tilde{\kappa}_t\rvert^*$	0.127	0.084	0.788	0.028	0.140	0.095	0.788	0.028	0.153	0.104	0.788	0.037
$\tilde{\kappa}_t^+$	0.127	0.079	0.526	0.029	0.140	0.086	0.526	0.029	0.155	0.098	0.526	0.044
$\tilde{\kappa}_t^-$	-0.128	0.088	-0.028	-0.788	-0.140	0.103	-0.028	-0.788	-0.152	0.109	-0.037	-0.788
$J\tilde{V}_{t,k}^*$	0.022	0.044	0.605	0.001	0.028	0.053	0.605	0.001	0.033	0.058	0.605	0.001
$J\tilde{V}_{t,k}^*/RV_t$	0.153	0.108	0.744	0.018	0.173	0.121	0.744	0.018	0.195	0.133	0.744	0.033
$J\tilde{V}D_t^*/RV_t$	0.203	0.124	0.774	0.041	0.215	0.135	0.774	0.045	0.239	0.147	0.774	0.045

Table 4.4.6.9. Summary Statistics for Sequential Intraday Jumps Using $BV_{1,t}$ and $TQ_{1,t}$ for Euro Bund Futures.

	$W_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	808	374	434	645	517	237	280	432	352	155	197	313
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\|\tilde{\kappa}_t\|$	0.000	0.007	0.613	0.000	0.000	0.006	0.613	0.000	0.000	0.006	0.613	0.000
$\|\tilde{\kappa}_t\|^*$	0.111	0.076	0.613	0.027	0.121	0.083	0.613	0.033	0.136	0.092	0.613	0.035
$\tilde{\kappa}_t^+$	0.110	0.074	0.574	0.033	0.118	0.079	0.574	0.033	0.132	0.086	0.574	0.035
$\tilde{\kappa}_t^-$	-0.112	0.078	-0.027	-0.613	-0.125	0.087	-0.033	-0.613	-0.140	0.096	-0.036	-0.613
$J\tilde{V}_{t,i}^*$	0.018	0.033	0.375	0.001	0.021	0.038	0.375	0.001	0.026	0.045	0.375	0.001
$J\tilde{V}_{t,i}^*/RV_t$	0.153	0.117	0.778	0.024	0.175	0.129	0.778	0.025	0.204	0.141	0.778	0.040
$J\tilde{V}D_t^*/RV_t$	0.192	0.124	0.824	0.032	0.210	0.135	0.824	0.045	0.229	0.142	0.778	0.046

	$Z_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	740	342	398	594	393	180	213	344	232	108	124	216
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\|\tilde{\kappa}_t\|$	0.000	0.007	0.613	0.000	0.000	0.006	0.613	0.000	0.000	0.006	0.613	0.000
$\|\tilde{\kappa}_t\|^*$	0.115	0.079	0.613	0.026	0.136	0.092	0.613	0.033	0.159	0.102	0.613	0.035
$\tilde{\kappa}_t^+$	0.113	0.078	0.574	0.026	0.132	0.088	0.574	0.035	0.151	0.095	0.574	0.035
$\tilde{\kappa}_t^-$	-0.117	0.080	-0.027	-0.613	-0.139	0.095	-0.033	-0.613	-0.165	0.108	-0.036	-0.613
$J\tilde{V}_{t,i}^*$	0.019	0.035	0.375	0.001	0.026	0.044	0.375	0.001	0.035	0.053	0.375	0.001
$J\tilde{V}_{t,i}^*/RV_t$	0.162	0.120	0.778	0.024	0.203	0.138	0.778	0.025	0.247	0.151	0.778	0.042
$J\tilde{V}D_t^*/RV_t$	0.202	0.129	0.910	0.045	0.232	0.142	0.824	0.046	0.265	0.156	0.824	0.052

	$U_{1,t}$											
α	0.01				0.001				0.0001			
	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$	$N(\|\tilde{\kappa}_t\|^*)$	$N(\tilde{\kappa}_t^+)$	$N(\tilde{\kappa}_t^-)$	$N(J\tilde{V}D^*)$
	703	322	381	567	393	178	215	346	248	113	135	226
	MEAN	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**	**MEAN**	**SD**	**MAX**	**MIN**
$\|\tilde{\kappa}_t\|$	0.000	0.007	0.613	0.000	0.000	0.006	0.613	0.000	0.000	0.005	0.613	0.000
$\|\tilde{\kappa}_t\|^*$	0.114	0.078	0.613	0.027	0.130	0.089	0.613	0.033	0.148	0.100	0.613	0.035
$\tilde{\kappa}_t^+$	0.112	0.075	0.574	0.033	0.124	0.083	0.574	0.035	0.140	0.091	0.574	0.035
$\tilde{\kappa}_t^-$	-0.115	0.080	-0.027	-0.613	-0.135	0.094	-0.033	-0.613	-0.154	0.107	-0.036	-0.613
$J\tilde{V}_{t,i}^*$	0.018	0.034	0.375	0.001	0.024	0.042	0.375	0.001	0.031	0.051	0.375	0.001
$J\tilde{V}_{t,i}^*/RV_t$	0.158	0.120	0.778	0.024	0.192	0.137	0.778	0.025	0.226	0.152	0.778	0.042
$J\tilde{V}D_t^*/RV_t$	0.196	0.126	0.824	0.032	0.219	0.139	0.778	0.045	0.248	0.153	0.778	0.046

Indeed, these comparisons across significant levels and alternative tests statistics provide results that are consistent across most series in this section, and therefore only deviations from these trends are highlighted in the following discussion.

Table 4.4.6.2 shows the results for GBP-USD futures. This market shows 364 jump days containing a total of 481 sequential intraday jumps, which is 242 more intraday jumps than for the EUR-USD market (note this sample also has a larger sample size), but this sequential method finds 228 fewer intraday jumps than the intraday jump method of section 4.4.5. The average absolute intraday jump size is 0.162, which is much smaller than under both the intraday jump technique of Table 4.4.5.2 and the EUR-USD futures market described above. Intraday jumps range from -0.720 to 0.683, which, surprisingly, means that the largest positive return of the sample measuring 0.749 is not identified as an intraday jump according to this sequential method. Average jump variation and relative jump contributions for individual jumps are 0.032 and 18.9%, respectively, and the average relative contribution of daily jump variation is 25%. These are all lower than found using the intraday jump detection method in Table 4.4.5.2 and also lower than for the EUR-USD contract in Table 4.4.6.1. The range of the relative daily jump variation measure is from 6.5% to 76.3%, which is lower than the previous intraday jump test. The sequential intraday jump method finds fewer jumps for GBP-USD and this evidence suggests that they are smaller and contribute less to overall variation.

The JPY-USD results in Table 4.4.6.3 complete the analysis of the foreign exchange futures markets. The table shows 234 days containing at least one jump and 253 intraday jumps in total for the $Z_{I,t}$ test statistic and α=0.001. This is 269 fewer jumps than identified by the intraday jump test of Table 4.4.5.3, only slightly more than identified for EUR-USD in Table 4.4.6.1, but a massive 228 fewer intraday jumps than identified for GBP-USD. There are also more positive than negative intraday jumps, as is found in the GBP-USD futures. Average absolute jump size is shown to be 0.244, which is only very slightly lower than the intraday jump test of Table 4.4.5.3 and the sequential method for the EUR-USD market, and is considerably higher than for the GBP-USD market in Table 4.4.6.2. Jumps range from -0.989 to 0.949, which correspond to the extreme jump values of Table 4.4.5.3, but the largest returns for the JPY-USD sample of -1.111 and 1.037 are not identified as intraday jumps by either of the methods. The mean jump variation of individual intraday jumps is 0.085 and these contribute 25.6% of total variation on average and this rises to 27.6% for the daily jump variation measure. These averages are all very similar to those of the intraday test of section 4.4.5, close to the EUR-USD figures and much higher than those for GBP-USD. Daily jump variation contribution to realised variation ranges from 5.9% to 87.3%, representing an extension on the lower side of the range as compared to the intraday test of Table 4.4.5.3. However, jumps can explain the vast majority of total variation on some days. For the foreign exchange futures markets in general, therefore, the sequential intraday jump detection method finds fewer intraday jumps than the intraday jump test of section 4.4.5, which generate smaller average jump sizes in absolute terms and smaller contributions to total variation.

Turning to the equity index futures, Table 4.4.6.4 displays the summary statistics for intraday jumps and related series identified by the sequential method for S&P 500 E-Mini futures. The panel for $Z_{1,t}$ and α=0.001 reveals 120 days containing jumps and 129 total intraday jumps so there are relatively few days showing multiple jumps. The test finds 236 fewer sequential intraday jumps than the method of section 4.4.5, and the S&P 500 E-Mini market shows fewer intraday jumps than the foreign exchange markets, despite being more volatile. Average absolute intraday jump size is 0.621, which is larger than for the intraday jumps in Table 4.4.5.4, showing that the fewer sequential intraday jumps detected retain the larger returns, and substantially larger than the corresponding means found for the foreign exchange futures markets. Jumps range from -2.884 to 5.584 showing that the largest returns of the sample are classified as sequential intraday jumps and these can be enormous. The minimum value of these jumps also indicates that large returns of either sign are identified as jumps. Jump variation has a mean of 0.835 during the significant intraday jump intervals and individual jumps contribute an average of 25.4% of realised variation. These averages are higher than those for the foreign exchange futures markets and the intraday jump test in Table 4.4.5.4, especially for the jump variation. Daily jump variation contributes an average 27.3% of realised variation on jump days, which is a high contribution, but is lower than that for EUR-USD futures. The range of this measure from 5.1% to 92.5% shows that some days show very large contributions to total variation whilst others show very little. The S&P 500 E-Mini market shows fewer jumps as compared to the foreign exchange markets, but these jumps are larger on average and generate higher jump variation, but do not provide vastly higher contributions to volatility on average. Standard deviations are noticeably higher for the S&P 500 E-Mini futures showing greater dispersion among the intraday jump series than for the foreign exchange markets, which is supported by the wider ranges between minimum and maximum values. The FTSE 100 futures market data show 193 sequential intraday jumps spread over 183 days, which is 64 more than the S&P 500 E-Mini, but less than the foreign exchange futures contracts and the sequential method finds 254 fewer jumps than the intraday jump test of the previous section. Average absolute sequential intraday jump size is 0.440, which is lower than the intraday jump method, lower than the S&P 500 E-Mini and higher than the foreign exchange futures markets for the same test method. Jumps range from -1.799 to 1.649, which do not correspond to the largest returns of the FTSE 100 sample. This means that the largest five-minute returns are not identified as sequential intraday jumps. Average jump variation is low given such a high average value for absolute jumps and, although this average is higher than in the foreign exchange markets, it is very much lower compared to that of the S&P 500 E-Mini market. The relative jump variation contribution is also low compared to other markets suggesting that the large jumps identified for FTSE 100 futures do not contribute towards realised daily variation to the same extent as for other markets.

The final market amongst the equity index futures is the DJ Euro Stoxx 50 futures contracts the results for which are shown in Table 4.4.6.6. The test finds 260 days containing a total of 310 jumps, which is 117 more than the FTSE 100, 181 more than the S&P 500 E-Mini and more than the EUR-USD and JPY-USD futures markets. The sequential intraday test finds 153 fewer jumps than the previous intraday jump test and the average size of absolute intraday jumps at 0.439 is slightly lower than the corresponding mean for raw returns in Table 4.4.5.6. This is similar to that of the FTSE 100, lower than for the S&P 500 E-Mini and higher than the foreign exchange futures under the same sequential method. The range of jumps, from -5.541 to 2.034, corresponds to the largest returns of the sample and show that occasional dramatic movements in prices are identified as jumps. The average jump variation of 0.401 is larger than for the FTSE 100 and foreign exchange futures markets, but smaller than for the S&P 500 E-Mini futures and lower than the corresponding average of the previous intraday jump test. Whilst the range of contributions to total variation is wide and suggests that these contributions can be high, the average contributions are disappointingly small, explaining on average 16.7% and 19.9% of total variation for individual jump variation and daily jump variation, respectively.

The DJ Euro Stoxx 50 futures, therefore, produce far more intraday jumps than the other two equity index futures markets and their means are relatively high. Their average contribution to total variation is very low, but the high maximum figures suggest that jumps are critical for realised variation on particular days. Standard deviations are also high for this market suggesting a wide dispersion of values around their means, which emphasises that some large and important jumps exist. Interestingly, for the case where α=0.0001, the largest return of the sample (-5.541) is not identified as an intraday jump whilst the maximum value of the jump variation contributions remain the same, showing that it is not necessarily the largest returns and largest intraday jumps that provide the strongest contributions to total variation.

The final collection of markets to consider is the interest rate futures markets. Table 4.4.6.7 shows the results for the US 10-Year Treasury Bond futures where the sequential intraday jump test finds 517 jumps over 354 days implying that there are many days containing multiple jumps. There are more negative than positive jumps. The sequential technique finds 79 fewer jumps than the intraday jumps test of section 4.4.5, but still finds a massive number of jumps, specifically 207 more than for the DJ Euro Stoxx 50 and 36 more than for the GBP-USD futures markets, which are the other markets exhibiting large numbers of sequential intraday jumps. The average size of the absolute sequential intraday jumps is 0.164, which is much smaller than in the previous intraday test results, despite the earlier method detecting more jumps in total. This average is also small compared to the other markets, with only the GBP-USD contract showing a similar value. Jumps fall in the range from -1.457 to 0.954, which are far less extreme than in the equity index futures markets. The smallest jumps are five-minute returns of -0.026 and 0.027, which mean that relatively small returns can be identified as jumps. Jump variation and the relative jump contribution of individual jumps show small averages of 0.054 and 22.6%, whereas the relative contribution of daily jump variation has an average of 33%, which is the highest of all markets considered so far. This large discrepancy between the relative contribution averages is likely to be due to the large number of days containing more than one jump for the US 10-Year T-Bond futures market. Average jumps are quite low, which is surprising given the large number of jumps identified, but the large daily contributions show that these jumps are no less important in the US 10-Year T-Bond market.

The UK Gilt futures show even more sequential intraday jumps than the US 10-Year T-Bond futures according to the results in Table 4.4.6.8, with 462 days containing jumps and 560 jumps in total. This represents 360 fewer jumps than the intraday jump test of the previous section, 43 more jumps than the US 10-Year T-Bond futures market and the highest number of sequential intraday jumps for all markets. Despite the presence of a large number of intraday jumps, the average size of their absolute value is only 0.146 and is the lowest of all markets. Jumps range from -0.788 to 0.526, which are low in magnitude compared to other markets. The largest positive five-minute return in the sample of 0.618 is not identified as a sequential intraday jump. The minimum jumps of -0.037 and 0.029 are also low in magnitude compared to other markets, which shows that some small returns are identified as sequential intraday jumps. Jump variation also shows the lowest average of all markets considered at 0.030 and the small jump contribution averages of 18.8% for individual jumps, and 22.8% for daily jump variation, are also smaller than the corresponding figures found for the simple intraday jump test. Only the DJ Euro Stoxx 50 futures market shows lower average relative jump contributions. These jumps, therefore, are small in magnitude and jump variation contributes less to total variation compared to other markets despite the UK Gilt futures showing more sequential intraday jumps than any other market.

Finally, Table 4.4.6.9 shows the results for the Euro Bund futures market, where the sequential intraday jump test detects 393 jumps on 344 days and these represent lower numbers of jumps than in the other two interest rate futures markets. There are far more negative jumps identified than positive jumps, 397 fewer sequential intraday jumps identified than compared to the intraday jump test of the previous section, 124 and 167 fewer jumps than the US 10-Year T-Bond and UK Gilt futures markets, but a larger number of jumps than all other remaining markets except for GBP-USD futures. The average size of the absolute sequential intraday jumps is 0.136, which is lower than for the intraday jump test results of Table 4.4.5.9 and is the lowest of all markets under this sequential jump detection method. Jumps range from -0.613 to 0.574, corresponding to the largest returns of the sample, however, this is a tight range compared to other markets, which helps to explain the low average jump size. Average jump variation is equivalent to that for the previous intraday jumps at 0.026 and this is perhaps surprising given that there are 397 fewer jumps identified under this sequential technique. This is also the lowest average jump variation across all markets. Relative jump contributions are 20.3% and 23.2% on average for individual and daily jump variation respectively, which are very similar to those for the intraday jump test of section 4.4.5, and are considerably lower than the corresponding results for the US 10-Year T-Bond and higher than those for the UK Gilt futures markets. The daily jump contribution has a maximum value of 82.4%, so although the average is quite low, there are days where jumps are critical components of total price variation.

Figures 4.4.6.1 to 4.4.6.3 summarise the number of days showing different numbers of intraday jumps for the foreign exchange, equity index and interest futures markets respectively. In confirmation of the discussion in the previous section, the vast majority of days containing jumps exhibit only a single sequential intraday jump. However, the following figures help to show that some days may be of particular interest since they show the presence of more than one jump. Concentrating on Z_I and α=0.001 as the preferred test specification, the EUR-USD market in Figure 4.4.6.1 shows at most 3 jumps on any particular day, and there are only 3 of these such days in the sample. With only 13 days showing 2 intraday jumps, the majority of jumps must occur on different days. A smaller significance level leads to fewer jumps being discovered and fewer days showing multiple jumps.

The GBP-USD futures market exhibits more jumps than the EUR-USD futures market and it is not surprising therefore that some days should show more than one jump. It is surprising, however, that some days show quite so many intraday jumps (10, 8, 6, 5 and 4 intraday jumps especially). These jumps are not eliminated by reducing the significance of the test either and these few days would provide some interesting case studies. The JPY-USD futures market is similar to the EUR-USD in showing only a maximum of 3 sequential intraday jumps in any one day and there is only one such day in the sample. Reducing the significance level generates at most 2 jumps in any day and there are only 2 such days identified. The foreign exchange market shows fewer jumps under the sequential method than the intraday jump test, but these patterns are very similar, with most days containing a single jump and occasional days showing 2 jumps, and days containing 3 jumps in rare cases. A notable exception is the GBP-USD market, which shows that individual days can hold up to 10 intraday jumps.

Figure 4.4.6.2 shows the same information for the equity index futures markets.

Figure 4.4.6.1. Sequential Intraday Jumps per Day Using $BV_{1,t}$ and $TQ_{1,t}$ for Foreign Exchange Futures.

EUR-USD

Intraday Jumps	$W_{1,t}$ α = 0.01	$W_{1,t}$ α = 0.001	$W_{1,t}$ α = 0.0001	$Z_{1,t}$ α = 0.01	$Z_{1,t}$ α = 0.001	$Z_{1,t}$ α = 0.0001	$U_{1,t}$ α = 0.01	$U_{1,t}$ α = 0.001	$U_{1,t}$ α = 0.0001
10	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
4	3	0	0	0	0	0	1	0	0
3	8	6	3	9	2	0	7	6	1
2	58	28	18	40	13	6	47	18	11
1	445	289	218	369	207	114	384	227	152

GBP-USD

Intraday Jumps	$W_{1,t}$ α = 0.01	$W_{1,t}$ α = 0.001	$W_{1,t}$ α = 0.0001	$Z_{1,t}$ α = 0.01	$Z_{1,t}$ α = 0.001	$Z_{1,t}$ α = 0.0001	$U_{1,t}$ α = 0.01	$U_{1,t}$ α = 0.001	$U_{1,t}$ α = 0.0001
12	1	0	0	1	0	0	1	0	0
11	0	1	0	0	0	0	0	0	0
10	0	0	0	0	1	0	0	1	0
9	0	0	0	1	0	0	0	0	1
8	1	0	0	0	1	1	0	0	0
7	1	1	1	0	0	1	1	0	0
6	1	1	1	2	2	0	1	2	0
5	7	3	1	4	1	2	4	0	2
4	11	8	6	7	5	1	13	9	4
3	49	25	15	36	10	7	34	16	10
2	128	88	61	108	52	20	109	62	39
1	521	380	306	456	292	196	466	313	237

JPY-USD

Intraday Jumps	$W_{1,t}$ α = 0.01	$W_{1,t}$ α = 0.001	$W_{1,t}$ α = 0.0001	$Z_{1,t}$ α = 0.01	$Z_{1,t}$ α = 0.001	$Z_{1,t}$ α = 0.0001	$U_{1,t}$ α = 0.01	$U_{1,t}$ α = 0.001	$U_{1,t}$ α = 0.0001
10	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
4	3	1	0	0	0	0	2	0	0
3	11	2	2	9	1	0	9	2	2
2	79	35	20	43	17	4	55	26	9
1	470	334	265	400	216	113	411	270	172

Figure 4.4.6.2. Sequential Intraday Jumps per Day Using $BV_{1,t}$ and $TQ_{1,t}$ for Equity Index Futures.

S&P 500 E-Mini

$W_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	5	1	0
2	37	14	12
1	310	203	123

$Z_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	1	0	0
2	22	9	1
1	271	111	55

$U_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	2	1	0
2	28	11	6
1	279	146	76

FTSE 100

$W_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	1	0	0
3	8	4	1
2	60	19	10
1	381	262	176

$Z_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	0	0	0
3	6	0	0
2	34	10	4
1	340	173	89

$U_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	1	0	0
3	4	1	0
2	50	15	8
1	340	193	112

DJ Euro Stoxx 50

$W_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	0	0
4	8	2	1
3	31	11	5
2	79	46	38
1	412	282	194

$Z_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	0	0	0
4	7	0	0
3	23	10	1
2	74	30	12
1	373	220	130

$U_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	0	0
4	6	1	0
3	23	7	4
2	70	37	21
1	366	224	142

Figure 4.4.6.3. Sequential Intraday Jumps per Day Using $BV_{1,t}$ and $TQ_{1,t}$ for Interest Rate Futures.

US 10-Year Treasury Bond

Intraday Jumps	$W_{1,t}$			$Z_{1,t}$			$U_{1,t}$		
α	0.01	0.001	0.0001	0.01	0.001	0.0001	0.01	0.001	0.0001
25	1						1		
24	0	1	1	1			0	1	
23	0	0	0	0	1		0	0	1
22	0	0	0	0	0		0	0	0
21	0	0	0	0	0	1	0	0	0
20	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0
16	0	0	0	1	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0
14	1	0	0	0	0	0	0	0	0
13	0	0	0	0	1	0	0	0	0
12	0	0	0	0	0	0	1	0	0
11	1	0	0	2	0	0	0	0	0
10	1	1	0	1	0	0	1	0	0
9	3	0	0	0	0	1	1	0	0
8	1	1	0	2	3	0	2	0	0
7	3	2	1	3	1	0	3	0	0
6	4	4	4	5	1	1	4	5	0
5	8	2	2	6	2	2	6	2	3
4	12	11	7	8	8	5	9	7	1
3	44	22	9	36	7	9	40	12	13
2	76	67	53	72	51	10	71	54	28
1	498	342	281	426	279	199	423	292	227

UK Gilt

Intraday Jumps	$W_{1,t}$			$Z_{1,t}$			$U_{1,t}$		
α	0.01	0.001	0.0001	0.01	0.001	0.0001	0.01	0.001	0.0001
10	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
8	1	0	0	0	0	0	0	0	0
7	1	1	0	1	0	0	2	1	0
6	2	1	2	2	1	1	2	1	2
5	2	2	0	4	1	0	1	1	0
4	11	4	4	8	6	2	10	3	2
3	40	17	9	27	10	7	33	11	8
2	156	93	60	135	51	27	121	69	36
1	606	460	341	575	393	231	570	388	257

Figure 4.4.6.3. (Continued)

Euro Bund

$W_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	0	0
4	6	2	0
3	21	9	4
2	99	61	31
1	518	360	278

$Z_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	2	0	0
4	5	0	0
3	18	7	2
2	87	35	12
1	482	302	202

$U_{1,t}$

Intraday Jumps	α = 0.01	α = 0.001	α = 0.0001
10	0	0	0
9	0	0	0
8	0	0	0
7	0	0	0
6	0	0	0
5	1	0	0
4	5	0	0
3	18	6	2
2	81	35	18
1	462	305	206

The plots show a similar pattern across all three markets in that most jumps occur on different days. There are at most 2 jumps on any given day for the S&P 500 E-Mini and FTSE 100 futures markets and a maximum of 3 intraday jumps on 10 of the days for the DJ Euro Stoxx 50 market.

Finally, Figure 4.4.6.3 presents the results for the interest rate futures markets.As with the other six markets, most jump days contain only a single sequential intraday jump, but the US 10-Year T-Bond futures market shows many days containing 2 jumps and very rare days containing 23, 13 jumps, or between 4 and 8 jumps. Most of these jumps remain identified when reducing the significance level of the test and under alternative specifications of the test. Whilst it is important to remember that days containing so many intraday jumps are very rare, they do provide interesting special cases in order to investigate the causes of these intraday jumps. This pattern for the US 10-Year T-Bond futures market is also different to the pattern presented for the simple intraday jump test in Figure 4.4.5.3, which displays at most 4 jumps in any one day. The UK Gilt futures also show occasional multi-jump days with a maximum of 6 sequential intraday jumps in any one day, which are all retained as α is reduced, and the Euro Bund market shows a maximum of 3 sequential intraday jumps on a given day, which is more in keeping with the foreign exchange and equity index markets.

In conclusion, therefore, this section has investigated the possibility of finding intraday jumps by way of an alternative sequential identification technique. Comparison with the intraday jump test of Andersen, Bollerslev and Dobrev (2007) analysed in the previous section shows that far fewer intraday jumps are detected by the sequential method, since the test restricts intraday jumps to be present only on significant jump days as governed by the daily jump test described and performed in section 4.4.4. Even with fewer jumps, the sequential intraday jump results show some huge jumps that contribute the majority of realised volatility on the days which they occur. The vast sizes of the jumps together with large relative contributions to total variation of daily jump variation confirm that the jumps are important components of the underlying price process. There is no claim as to which intraday jump detection technique is superior, for this will depend on the timings of jumps and relating these times to possible causes of the jumps in order to determine whether they are correctly identified. There is a preference, however, for the intraday jump detection method of Andersen, Bollerslev and Dobrev (2007) since it does not constrain intraday jumps to occur on significant jump days as dictated by the daily jump tests of section 4.4.4. It is interesting that the largest five-minute returns of the samples do not always correspond to intraday jumps, which implies that jumps are indeed identified in the context of daily realised and bipower variation and not purely on the magnitude of intraday price movements. Finally, there are very many jumps identified at the daily and intraday level, which supports that claim that jumps are an important feature of the underlying price process, and also gives a wider scope to address the causes of these jumps. Previous research suggests that the large intraday returns often follow the arrival of new information, or news, which causes traders and investors to revalue their expectations, asset valuations, and portfolio holdings. Macroeconomic news announcements provide one such source of public news and with many macroeconomic indicators announced frequently, it seems intuitive to attempt to link the arrival of macroeconomic news with asset price jumps and this is the aim of the following section and the major contribution of this work.

4.5 JUMPS AND NEWS

4.5.1 Largest Jumps and News

As a preliminary step in investigating the relationship between jumps and macroeconomic news announcements, Tables 4.5.1.1 to 4.5.1.9 display the largest daily jump variation measures and the largest absolute intraday jumps for each futures market and for a range of jump measures. More specifically, the top panel in each table shows the twelve largest daily jump variation measures as measured by the non-negative condition of equation (4.15) and the twelve largest and statistically significant (α=0.001), jump variation days measured according to the $Z_{I,t}$ test statistic of equations (4.28), (4.33) and (4.34). The second panel shows the fifteen largest absolute intraday jumps for raw returns and returns standardised by average absolute returns as measured by the Andersen, Bollerslev and Dobrev (2007) method given in equation (4.36) for α=0.001. The third panel illustrates the fifteen largest absolute intraday jumps as measured by the sequential detection method of Andersen, Bollerslev, Frederiksen and Nielsen (2006) for the $Z_{I,t}$ and $U_{I,t}$ versions of the test according to equations (4.37) and (4.38). The two lower panels show the exact timing of intraday jumps and details how the jumps are associated with US macroeconomic news announcements occurring at the same time.

Table 4.5.1.1. Largest Jumps and News for EUR-USD Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
7	5	2004	1.84	7	5	2004	1.84
5	3	2004	0.98	5	3	2004	0.98
9	1	2004	0.66	9	1	2004	0.66
3	1	2001	0.65	3	1	2001	0.65
11	3	1999	0.52	11	3	1999	0.52
30	1	2004	0.47	30	1	2004	0.47
12	1	2005	0.47	12	1	2005	0.47
7	9	2001	0.44	7	9	2001	0.44
5	9	2003	0.41	5	9	2003	0.41
6	8	2004	0.35	6	8	2004	0.35
9	11	2000	0.33	9	11	2000	0.33
2	7	2004	0.31	2	7	2004	0.31

Intraday Jumps (Raw Returns)							Intraday Jumps (Standardised Returns)							
DATE			TIME		κ_k	NEWS	DATE			TIME		κ_k	NEWS
7	5	2004	7	35	-1.379	Employment Report	7	5	2004	7	35	-1.379	Employment Report
5	3	2004	7	35	0.948	Employment Report	5	3	2004	7	35	0.948	Employment Report
9	1	2004	7	35	0.862	Employment Report	9	1	2004	7	35	0.862	Employment Report
11	3	1999	10	50	0.861		11	3	1999	10	50	0.861	
12	1	2005	7	35	0.774	Trade Balance	12	1	2005	7	35	0.774	Trade Balance
7	9	2001	7	35	0.768	Employment Report	7	9	2001	7	35	0.768	Employment Report
30	1	2004	7	35	0.749	GDP Advance	30	1	2004	7	35	0.749	GDP Advance
19	7	1999	11	30	0.716		19	7	1999	11	30	0.716	
6	8	2004	7	35	0.707	Employment Report	6	8	2004	7	35	0.707	Employment Report
3	1	2001	12	20	-0.688	FOMC	3	1	2001	12	20	-0.688	FOMC
4	6	2004	7	45	0.646	Employment Report	4	6	2004	7	45	0.646	Employment Report
9	11	2000	8	50	0.604		9	11	2000	8	50	0.604	
4	4	2000	12	0	0.598		5	9	2003	7	35	0.585	Employment Report
5	1	2001	7	35	-0.587	Employment Report	2	7	2004	7	35	0.572	Employment Report
5	9	2003	7	35	0.585	Employment Report	27	3	2001	9	5	-0.558	Consumer Confidence

Sequential Intraday Jumps

DATE			TIME		$\widetilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\widetilde{\kappa}_k(U_{1,t})$	NEWS
7	5	2004	7	35	-1.379	Employment Report	7	5	2004	7	35	-1.379	Employment Report
5	3	2004	7	35	0.948	Employment Report	5	3	2004	7	35	0.948	Employment Report
9	1	2004	7	35	0.862	Employment Report	9	1	2004	7	35	0.862	Employment Report
11	3	1999	10	50	0.861		11	3	1999	10	50	0.861	
12	1	2005	7	35	0.774	Trade Balance	12	1	2005	7	35	0.774	Trade Balance
7	9	2001	7	35	0.768	Employment Report	7	9	2001	7	35	0.768	Employment Report
30	1	2004	7	35	0.749	GDP Advance	30	1	2004	7	35	0.749	GDP Advance
6	8	2004	7	35	0.707	Employment Report	3	1	2001	12	20	-0.688	FOMC
3	1	2001	12	20	-0.688	FOMC	9	11	2000	8	50	0.604	
9	11	2000	8	50	0.604		5	9	2003	7	35	0.585	Employment Report
5	9	2003	7	35	0.585	Employment Report	2	7	2004	7	35	0.572	Employment Report
2	7	2004	7	35	0.572	Employment Report	27	3	2001	9	5	-0.558	Consumer Confidence
27	3	2001	9	5	-0.558	Consumer Confidence	2	4	2004	7	35	-0.556	Employment Report
2	4	2004	7	35	-0.556	Employment Report	29	3	2000	9	5	-0.544	New Homes Sales
29	3	2000	9	5	-0.544	New Homes Sales	7	2	2003	7	35	-0.540	Employment Report

Table 4.5.1.2. Largest Jumps and News for GBP-USD Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
7	5	2004	0.46	7	5	2004	0.46
6	8	2004	0.41	6	8	2004	0.41
2	4	2004	0.37	2	4	2004	0.37
12	1	2005	0.27	12	1	2005	0.27
7	9	2001	0.26	7	9	2001	0.26
5	5	2006	0.23	5	5	2006	0.23
2	7	2004	0.22	2	7	2004	0.22
30	1	2004	0.22	30	1	2004	0.22
9	1	2004	0.18	9	1	2004	0.18
19	7	1999	0.16	4	2	2005	0.15
4	2	2005	0.15	16	10	2000	0.15
16	10	2000	0.15	27	10	2000	0.15

Intraday Jumps (Raw Returns)							Intraday Jumps (Standardised Returns)						
DATE			TIME		κ_k	NEWS	DATE			TIME		κ_k	NEWS
19	7	1999	11	30	0.749		19	7	1999	11	30	0.749	
7	5	2004	7	35	-0.720	Employment Report	7	5	2004	7	35	-0.720	Employment Report
6	8	2004	7	35	0.683	Employment Report	6	8	2004	7	35	0.683	Employment Report
2	4	2004	7	35	-0.590	Employment Report	2	4	2004	7	35	-0.590	Employment Report
30	1	2004	7	35	0.586	GDP Advance	30	1	2004	7	35	0.586	GDP Advance
2	7	2004	7	35	0.585	Employment Report	2	7	2004	7	35	0.585	Employment Report
12	1	2005	7	35	0.582	Trade Balance	12	1	2005	7	35	0.582	Trade Balance
5	3	2004	7	35	0.554	Employment Report	7	9	2001	7	35	0.535	Employment Report
7	9	2001	7	35	0.535	Employment Report	5	5	2006	7	35	0.501	Employment Report
5	5	2006	7	35	0.501	Employment Report	8	10	2004	7	35	0.494	Employment Report
8	10	2004	7	35	0.494	Employment Report	9	1	2004	7	35	0.487	Employment Report
9	1	2004	7	35	0.487	Employment Report	10	1	2003	7	35	0.399	Employment Report
5	9	2003	7	35	0.405	Employment Report	10	3	2004	7	45	-0.394	Trade Balance
10	1	2003	7	35	0.399	Employment Report	6	8	2004	7	30	0.385	Employment Report
10	3	2004	7	45	-0.394	Trade Balance	6	2	2004	7	50	0.380	Employment Report

Sequential Intraday Jumps

DATE			TIME		$\widetilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\widetilde{\kappa}_k(U_{1,t})$	NEWS
7	5	2004	7	35	-0.720	Employment Report	7	5	2004	7	35	-0.720	Employment Report
6	8	2004	7	35	0.683	Employment Report	6	8	2004	7	35	0.683	Employment Report
2	4	2004	7	35	-0.590	Employment Report	2	4	2004	7	35	-0.590	Employment Report
30	1	2004	7	35	0.586	GDP Advance	30	1	2004	7	35	0.586	GDP Advance
2	7	2004	7	35	0.585	Employment Report	2	7	2004	7	35	0.585	Employment Report
12	1	2005	7	35	0.582	Trade Balance	12	1	2005	7	35	0.582	Trade Balance
7	9	2001	7	35	0.535	Employment Report	7	9	2001	7	35	0.535	Employment Report
5	5	2006	7	35	0.501	Employment Report	5	5	2006	7	35	0.501	Employment Report
9	1	2004	7	35	0.487	Employment Report	9	1	2004	7	35	0.487	Employment Report
5	9	2003	7	35	0.405	Employment Report	5	9	2003	7	35	0.405	Employment Report
10	1	2003	7	35	0.399	Employment Report	10	1	2003	7	35	0.399	Employment Report
9	6	2006	7	35	-0.375	Trade Balance	9	6	2006	7	35	-0.375	Trade Balance
23	3	2005	7	35	-0.359	CPI	23	3	2005	7	35	-0.359	CPI
28	12	2005	11	10	-0.355		29	6	2006	13	20	0.352	FOMC
29	6	2006	13	20	0.352	FOMC	4	2	2005	7	35	0.350	Employment Report

Table 4.5.1.3. Largest Jumps and News for JPY-USD Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
8	10	1998	1.36	7	10	1998	1.29
7	10	1998	1.29	12	11	1998	0.92
12	11	1998	0.92	28	6	2002	0.79
28	6	2002	0.79	20	7	1999	0.59
20	7	1999	0.59	6	8	2004	0.58
6	8	2004	0.58	5	11	2004	0.52
5	11	2004	0.52	12	5	1999	0.50
12	5	1999	0.50	2	7	2004	0.45
2	7	2004	0.45	4	6	2002	0.43
4	6	2002	0.43	7	5	2004	0.37
7	5	2004	0.37	12	1	2005	0.36
12	1	2005	0.36	22	7	1999	0.36

Intraday Jumps (Raw Returns)							Intraday Jumps (Standardised Returns)						
DATE			TIME		κ_k	NEWS	DATE			TIME		κ_k	NEWS
28	6	2002	9	5	-0.989	Chicago PMI	28	6	2002	9	5	-0.989	Chicago PMI
7	10	1998	13	45	0.949		7	10	1998	13	45	0.949	
20	7	1999	8	10	-0.943	Trade Balance	20	7	1999	8	10	-0.943	Trade Balance
12	11	1998	11	5	0.889		12	11	1998	11	5	0.889	
6	8	2004	7	35	0.787	Employment Report	6	8	2004	7	35	0.787	Employment Report
28	1	2000	10	40	-0.763		28	1	2000	10	40	-0.763	
12	5	1999	8	50	0.759		12	5	1999	8	50	0.759	
12	1	2005	7	35	0.757	Trade Balance	12	1	2005	7	35	0.757	Trade Balance
2	7	2004	7	35	0.748	Employment Report	2	7	2004	7	35	0.748	Employment Report
7	5	2004	7	35	-0.740	Employment Report	7	5	2004	7	35	-0.740	Employment Report
4	6	2002	7	35	-0.693		4	6	2002	7	35	-0.693	
4	6	2004	7	45	0.666	Employment Report	4	6	2004	7	45	0.666	Employment Report
5	11	2004	7	30	-0.638	Employment Report	5	11	2004	7	30	-0.638	Employment Report
5	5	2006	7	35	0.633	Employment Report	5	5	2006	7	35	0.633	Employment Report
6	12	2002	8	25	0.615		6	12	2002	8	25	0.615	

Sequential Intraday Jumps

DATE			TIME		$\widetilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\widetilde{\kappa}_k(U_{1,t})$	NEWS
28	6	2002	9	5	-0.989	Chicago PMI	28	6	2002	9	5	-0.989	Chicago PMI
7	10	1998	13	45	0.949		20	7	1999	8	10	-0.943	Trade Balance
20	7	1999	8	10	-0.943	Trade Balance	12	11	1998	11	5	0.889	
12	11	1998	11	5	0.889		6	8	2004	7	35	0.787	Employment Report
6	8	2004	7	35	0.787	Employment Report	28	1	2000	10	40	-0.763	
28	1	2000	10	40	-0.763		12	5	1999	8	50	0.759	
12	5	1999	8	50	0.759		12	1	2005	7	35	0.757	Trade Balance
12	1	2005	7	35	0.757	Trade Balance	2	7	2004	7	35	0.748	Employment Report
2	7	2004	7	35	0.748	Employment Report	7	5	2004	7	35	-0.740	Employment Report
7	5	2004	7	35	-0.740	Employment Report	4	6	2002	7	35	-0.693	
4	6	2002	7	35	-0.693		5	11	2004	7	30	-0.638	Employment Report
5	11	2004	7	30	-0.638	Employment Report	5	5	2006	7	35	0.633	Employment Report
5	5	2006	7	35	0.633	Employment Report	30	9	1999	9	45	-0.535	Chicago PMI
30	9	1999	9	45	-0.535	Chicago PMI	7	9	2001	7	35	0.531	Employment Report
7	9	2001	7	35	0.531	Employment Report	6	1	2006	7	50	0.527	Employment Report

Table 4.5.1.4. Largest Jumps and News for S&P 500 E-Mini Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
15	10	1998	35.22	15	10	1998	35.22
18	4	2001	7.56	18	4	2001	7.56
3	1	2001	4.13	3	1	2001	4.13
8	12	2000	3.58	8	12	2000	3.58
2	6	2000	3.08	2	6	2000	3.08
28	1	2000	2.65	28	1	2000	2.65
12	5	1999	2.41	12	5	1999	2.41
12	11	2001	2.25	12	11	2001	2.25
7	3	2003	2.14	7	3	2003	2.14
30	6	1999	1.88	30	6	1999	1.88
10	1	2003	1.66	10	1	2003	1.66
31	8	1998	1.63	27	4	2000	1.45

Intraday Jumps (Raw Returns)

DATE			TIME		κ_k	NEWS
15	10	1998	14	20	5.584	FOMC
18	4	2001	10	0	2.908	FOMC
15	10	1998	14	25	-2.884	FOMC
8	12	2000	15	5	-2.359	
2	6	2000	7	35	2.063	Employment Report
12	5	1999	8	50	-1.989	
3	1	2001	12	20	1.935	FOMC
28	1	2000	7	35	-1.669	GDP Advance
3	1	2001	12	15	1.645	FOMC
10	1	2003	7	35	-1.486	Employment Report
7	3	2003	9	15	1.399	
30	6	1999	13	20	1.395	FOMC
12	11	2001	8	30	-1.366	
6	12	2002	7	35	-1.304	Employment Report
27	4	2000	7	35	-1.299	GDP Advance

Intraday Jumps (Standardised Returns)

DATE			TIME		κ_k	NEWS
15	10	1998	14	20	5.584	FOMC
18	4	2001	10	0	2.908	FOMC
15	10	1998	14	25	-2.884	FOMC
8	12	2000	15	5	-2.359	
2	6	2000	7	35	2.063	Employment Report
12	5	1999	8	50	-1.989	
3	1	2001	12	20	1.935	FOMC
28	1	2000	7	35	-1.669	GDP Advance
3	1	2001	12	15	1.645	FOMC
10	1	2003	7	35	-1.486	Employment Report
4	4	2000	12	10	-1.485	
7	3	2003	9	15	1.399	
30	6	1999	13	20	1.395	FOMC
12	11	2001	8	30	-1.366	
6	12	2002	7	35	-1.304	Employment Report

Sequential Intraday Jumps

DATE			TIME		$\tilde{\kappa}_k(Z_{1,t})$	NEWS
15	10	1998	14	20	5.584	FOMC
18	4	2001	10	0	2.908	FOMC
15	10	1998	14	25	-2.884	FOMC
8	12	2000	15	5	-2.359	
2	6	2000	7	35	2.063	Employment Report
12	5	1999	8	50	-1.989	
3	1	2001	12	20	1.935	FOMC
28	1	2000	7	35	-1.669	GDP Advance
10	1	2003	7	35	-1.486	Employment Report
7	3	2003	9	15	1.399	
30	6	1999	13	20	1.395	FOMC
12	11	2001	8	30	-1.366	
6	12	2002	7	35	-1.304	Employment Report
27	4	2000	7	35	-1.299	GDP Advance
6	11	2002	13	35	-1.182	FOMC

DATE			TIME		$\tilde{\kappa}_k(U_{1,t})$	NEWS
15	10	1998	14	20	5.584	FOMC
18	4	2001	10	0	2.908	FOMC
15	10	1998	14	25	-2.884	FOMC
8	12	2000	15	5	-2.359	
2	6	2000	7	35	2.063	Employment Report
12	5	1999	8	50	-1.989	
28	1	2000	7	35	-1.669	GDP Advance
10	1	2003	7	35	-1.486	Employment Report
7	3	2003	9	15	1.399	
30	6	1999	13	20	1.395	FOMC
12	11	2001	8	30	-1.366	
6	12	2002	7	35	-1.304	Employment Report
27	4	2000	7	35	-1.299	GDP Advance
5	11	1999	7	35	1.160	Employment Report
7	9	2001	7	35	-1.158	Employment Report

Table 4.5.1.5. Largest Jumps and News for FTSE 100 Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
12	11	2001	2.72	12	11	2001	2.72
12	9	2001	2.52	5	4	2000	2.47
5	4	2000	2.47	12	5	1999	2.38
12	5	1999	2.38	24	9	2001	2.15
24	9	2001	2.15	27	8	1998	1.62
11	9	2001	1.93	31	7	2002	1.53
27	8	1998	1.62	6	12	2002	1.38
31	7	2002	1.53	26	9	2002	1.35
6	12	2002	1.38	11	10	2001	1.25
26	9	2002	1.35	17	2	2000	1.12
11	10	2001	1.25	4	4	2001	1.01
17	2	2000	1.12	3	9	1999	0.91

Intraday Jumps (Raw Returns) / **Intraday Jumps (Standardised Returns)**

DATE			TIME		κ_k	NEWS	DATE			TIME		κ_k	NEWS
11	9	2001	14	45	-3.108	Terrorist Attacks	11	9	2001	14	45	-3.108	Terrorist Attacks
12	11	2001	14	35	-1.799		12	11	2001	14	35	-1.799	
12	5	1999	14	50	-1.717		12	5	1999	14	50	-1.717	
12	9	2001	8	30	1.666		24	9	2001	8	10	1.517	
5	4	2000	8	5	1.649		20	9	2002	10	15	1.508	
12	9	2001	8	35	1.556		6	12	2002	13	35	-1.337	Employment Report
24	9	2001	8	10	1.517		27	8	1998	16	50	-1.312	
20	9	2002	10	15	1.508		7	7	2005	10	20	-1.250	
6	12	2002	13	35	-1.337	Employment Report	6	9	2002	13	35	1.179	Employment Report
27	8	1998	16	50	-1.312		12	7	2002	14	50	-1.148	Mich. Sentiment (P)
7	7	2005	10	20	-1.250		26	9	2002	13	40	1.115	Durable Goods
27	9	2002	8	25	1.180		10	1	2003	13	35	-1.064	Employment Report
6	9	2002	13	35	1.179	Employment Report	27	4	2000	13	35	-1.012	GDP Advance
12	7	2002	14	50	-1.148	Mich. Sentiment (P)	17	2	2000	15	5	-1.000	Philly Fed Index
26	9	2002	13	40	1.115	Durable Goods	3	12	1998	13	5	0.992	

Sequential Intraday Jumps

DATE			TIME		$\widetilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\widetilde{\kappa}_k(U_{1,t})$	NEWS
12	11	2001	14	35	-1.799		12	11	2001	14	35	-1.799	
12	5	1999	14	50	-1.717		12	5	1999	14	50	-1.717	
5	4	2000	8	5	1.649		5	4	2000	8	5	1.649	
24	9	2001	8	10	1.517		24	9	2001	8	10	1.517	
6	12	2002	13	35	-1.337	Employment Report	6	12	2002	13	35	-1.337	Employment Report
27	8	1998	16	50	-1.312		27	8	1998	16	50	-1.312	
26	9	2002	13	40	1.115	Durable Goods	26	9	2002	13	40	1.115	Durable Goods
10	1	2003	13	35	-1.064	Employment Report	10	1	2003	13	35	-1.064	Employment Report
24	3	2003	8	5	-1.040		17	2	2000	15	5	-1.000	Philly Fed Index
11	10	2001	8	5	1.037		2	6	2000	13	35	0.976	Employment Report
17	2	2000	15	5	-1.000	Philly Fed Index	3	9	1999	13	35	0.927	Employment Report
2	6	2000	13	35	0.976	Employment Report	3	2	2003	8	5	0.898	
3	9	1999	13	35	0.927	Employment Report	13	3	2000	8	5	0.897	
3	2	2003	8	5	0.898		31	7	2002	8	30	0.890	
13	3	2000	8	5	0.897		28	10	1999	13	35	0.878	GDP Advance

Table 4.5.1.6. Largest Jumps and News for DJ Euro Stoxx 50 Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
11	9	2001	16.15	11	9	2001	16.15
25	9	2002	7.16	25	9	2002	7.16
24	7	2002	6.11	12	11	2001	4.28
12	11	2001	4.28	6	8	2002	4.02
6	8	2002	4.02	6	9	2002	3.74
25	7	2002	3.84	7	9	2001	3.18
6	9	2002	3.74	22	4	2003	3.02
7	9	2001	3.18	3	10	2002	2.91
22	4	2003	3.02	27	12	2002	2.05
3	10	2002	2.91	10	1	2003	1.98
6	12	2002	2.38	3	9	1999	1.90
27	12	2002	2.05	13	11	2002	1.85

Intraday Jumps (Raw Returns)								Intraday Jumps (Standardised Returns)							
DATE			TIME		κ_k	NEWS		DATE			TIME		κ_k	NEWS	
11	9	2001	15	45	-5.541	Terrorist Attacks		11	9	2001	15	45	-5.541	Terrorist Attacks	
12	11	2001	15	35	-2.745			12	11	2001	15	35	-2.745		
6	12	2002	14	35	-2.213	Employment Report		6	12	2002	14	35	-2.213	Employment Report	
25	9	2002	10	5	2.034			25	9	2002	10	5	2.034		
25	9	2002	19	55	1.987			25	9	2002	19	55	1.987		
6	9	2002	14	35	1.925	Employment Report		6	9	2002	14	35	1.925	Employment Report	
26	7	2002	15	50	1.803	Mich. Sentiment (R)		7	9	2001	14	35	-1.601	Employment Report	
25	7	2002	16	15	1.761	New Home Sales		22	4	2003	19	15	1.527		
24	9	2002	16	5	1.740	Consumer Confidence		15	10	1999	14	35	-1.512	PPI	
31	7	2002	14	35	-1.635	GDP Advance		14	6	2002	15	55	-1.450	Mich. Sentiment (P)	
7	9	2001	14	35	-1.601	Employment Report		10	1	2003	14	35	-1.439	Employment Report	
22	4	2003	19	15	1.527			2	4	2004	15	35	1.416		
15	10	1999	14	35	-1.512	PPI		6	8	2002	10	5	1.397		
12	7	2002	15	50	-1.477	Mich. Sentiment (P)		3	9	1999	14	35	1.385	Employment Report	
14	6	2002	15	55	-1.450	Mich. Sentiment (P)		13	11	2002	16	50	1.364		

Sequential Intraday Jumps

DATE			TIME		$\tilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\tilde{\kappa}_k(U_{1,t})$	NEWS
11	9	2001	15	45	-5.541	Terrorist Attacks	25	9	2002	10	5	2.034	
12	11	2001	15	35	-2.745		6	9	2002	14	35	1.925	Employment Report
25	9	2002	10	5	2.034		24	8	2001	14	35	-1.601	Durable Goods
6	9	2002	14	35	1.925	Employment Report	22	4	2003	19	15	1.527	
7	9	2001	14	35	-1.601	Employment Report	15	10	1999	14	35	-1.512	PPI
22	4	2003	19	15	1.527		14	6	2002	15	55	-1.450	Mich. Sentiment (P)
15	10	1999	14	35	-1.512	PPI	10	1	2003	14	35	-1.439	Employment Report
14	6	2002	15	55	-1.450	Mich. Sentiment (P)	2	4	2004	15	35	1.416	
10	1	2003	14	35	-1.439	Employment Report	6	8	2002	10	5	1.397	
2	4	2004	15	35	1.416		3	9	1999	14	35	1.385	Employment Report
6	8	2002	10	5	1.397		13	11	2002	16	50	1.364	
3	9	1999	14	35	1.385	Employment Report	19	5	2000	14	35	1.304	Trade Balance
13	11	2002	16	50	1.364		27	8	2002	14	35	1.265	
2	6	2000	14	35	1.304	Employment Report	18	1	1999	10	20	1.251	
27	8	2002	14	35	1.265	Durable Goods	3	10	2002	16	5	1.235	Factory Orders

Table 4.5.1.7. Largest Jumps and News for US 10-Year T-Bond Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
2	4	2004	1.24	2	4	2004	1.24
7	11	2003	1.06	7	11	2003	1.06
6	8	2004	0.95	6	8	2004	0.95
9	1	2004	0.79	9	1	2004	0.79
5	3	2004	0.58	5	3	2004	0.58
5	12	2003	0.50	5	12	2003	0.50
7	5	2004	0.46	7	5	2004	0.46
30	6	1999	0.43	30	6	1999	0.43
6	8	1999	0.42	6	8	1999	0.42
2	6	2000	0.41	2	6	2000	0.41
5	11	2004	0.38	5	11	2004	0.38
31	7	2003	0.37	31	7	2003	0.37

Intraday Jumps (Raw Returns)							Intraday Jumps (Standardised Returns)						
DATE			TIME		κ_k	NEWS	DATE			TIME		κ_k	NEWS
2	4	2004	7	35	-1.457	Employment Report	2	4	2004	7	35	-1.457	Employment Report
7	11	2003	7	35	-1.067	Employment Report	7	11	2003	7	35	-1.067	Employment Report
9	1	2004	7	35	0.954	Employment Report	9	1	2004	7	35	0.954	Employment Report
6	8	2004	7	30	0.949	Employment Report	6	8	2004	7	30	0.949	Employment Report
2	6	2000	7	35	0.942	Employment Report	2	6	2000	7	35	0.942	Employment Report
5	3	2004	7	35	0.875	Employment Report	5	3	2004	7	35	0.875	Employment Report
30	6	1999	13	20	0.792	FOMC	30	6	1999	13	20	0.792	FOMC
7	5	2004	7	35	-0.772	Employment Report	7	5	2004	7	35	-0.772	Employment Report
5	12	2003	7	35	0.772	Employment Report	5	12	2003	7	35	0.772	Employment Report
6	12	2002	7	35	0.724	Employment Report	6	2	2004	7	35	0.675	Employment Report
6	2	2004	7	35	0.675	Employment Report	5	11	2004	7	30	-0.665	Employment Report
5	11	2004	7	30	-0.665	Employment Report	6	8	1999	7	45	-0.624	Employment Report
3	10	2003	7	35	-0.661	Employment Report	30	10	2003	7	35	-0.613	GDP Advance
5	3	1999	7	35	0.629	Employment Report	28	1	2004	13	20	-0.592	FOMC
31	7	2003	7	35	-0.628	Initial Claims	13	3	2002	7	35	0.592	Retail Sales

Sequential Intraday Jumps

DATE			TIME		$\widetilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\widetilde{\kappa}_k(U_{1,t})$	NEWS
2	4	2004	7	35	-1.457	Employment Report	2	4	2004	7	35	-1.457	Employment Report
7	11	2003	7	35	-1.067	Employment Report	7	11	2003	7	35	-1.067	Employment Report
9	1	2004	7	35	0.954	Employment Report	9	1	2004	7	35	0.954	Employment Report
6	8	2004	7	30	0.949	Employment Report	6	8	2004	7	30	0.949	Employment Report
2	6	2000	7	35	0.942	Employment Report	5	3	2004	7	35	0.875	Employment Report
5	3	2004	7	35	0.875	Employment Report	30	6	1999	13	20	0.792	FOMC
30	6	1999	13	20	0.792	FOMC	7	5	2004	7	35	-0.772	Employment Report
7	5	2004	7	35	-0.772	Employment Report	5	12	2003	7	35	0.772	Employment Report
5	12	2003	7	35	0.772	Employment Report	6	2	2004	7	35	0.675	Employment Report
6	2	2004	7	35	0.675	Employment Report	5	11	2004	7	30	-0.665	Employment Report
5	11	2004	7	30	-0.665	Employment Report	3	10	2003	7	35	-0.661	Employment Report
3	10	2003	7	35	-0.661	Employment Report	31	7	2003	7	35	-0.628	Initial Claims
31	7	2003	7	35	-0.628	Initial Claims	6	8	1999	7	45	-0.624	Employment Report
6	8	1999	7	45	-0.624	Employment Report	10	1	2003	7	35	0.623	Employment Report
10	1	2003	7	35	0.623	Employment Report	30	10	2003	7	35	-0.613	GDP Advance

Table 4.5.1.8. Largest Jumps and News for UK Gilt Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
9	10	1998	1.01	9	10	1998	1.01
14	12	2000	0.34	14	12	2000	0.34
7	5	2004	0.27	7	5	2004	0.27
6	9	2002	0.24	6	9	2002	0.24
12	11	2001	0.24	12	11	2001	0.24
2	6	2000	0.24	2	6	2000	0.24
2	4	2004	0.21	2	4	2004	0.21
11	3	1999	0.20	11	3	1999	0.20
9	1	2004	0.20	9	1	2004	0.20
26	7	1999	0.18	26	7	1999	0.18
28	10	1999	0.18	28	10	1999	0.18
27	9	1999	0.17	27	9	1999	0.17

Intraday Jumps (Raw Returns) / **Intraday Jumps (Standardised Returns)**

DATE			TIME		κ_k	NEWS	DATE			TIME		κ_k	NEWS
9	10	1998	8	10	-0.788		9	10	1998	8	10	-0.788	
2	4	2004	14	30	-0.749		2	4	2004	14	30	-0.749	
7	5	2004	13	35	-0.620	Employment Report	7	5	2004	13	35	-0.620	Employment Report
9	10	1998	8	15	-0.618		9	10	1998	8	15	-0.618	
9	10	1998	8	30	0.618		9	10	1998	8	30	0.618	
3	9	1999	13	35	0.526	Employment Report	3	9	1999	13	35	0.526	Employment Report
9	1	2004	13	35	0.514	Employment Report	9	1	2004	13	35	0.514	Employment Report
14	12	2000	11	20	-0.514		14	12	2000	11	20	-0.514	
3	9	2004	13	35	-0.497	Employment Report	3	9	2004	13	35	-0.497	Employment Report
12	11	2001	14	35	0.488		12	11	2001	14	35	0.488	
3	10	2003	13	35	-0.478	Employment Report	3	10	2003	13	35	-0.478	Employment Report
2	4	2004	14	40	0.464		2	4	2004	14	40	0.464	
20	8	1999	16	35	0.452		20	8	1999	16	35	0.452	
8	9	1999	12	5	-0.446	MPC	8	9	1999	12	5	-0.446	MPC
11	3	1999	17	5	0.436		11	3	1999	17	5	0.436	

Sequential Intraday Jumps

DATE			TIME		$\widetilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\widetilde{\kappa}_k(U_{1,t})$	NEWS
9	10	1998	8	10	-0.788		9	10	1998	8	10	-0.788	
2	4	2004	14	30	-0.749		2	4	2004	14	30	-0.749	
7	5	2004	13	35	-0.620	Employment Report	7	5	2004	13	35	-0.620	Employment Report
3	9	1999	13	35	0.526	Employment Report	9	10	1998	8	15	-0.618	
9	1	2004	13	35	0.514	Employment Report	3	9	1999	13	35	0.526	Employment Report
14	12	2000	11	20	-0.514		9	1	2004	13	35	0.514	Employment Report
3	9	2004	13	35	-0.497	Employment Report	14	12	2000	11	20	-0.514	
12	11	2001	14	35	0.488		3	9	2004	13	35	-0.497	Employment Report
3	10	2003	13	35	-0.478	Employment Report	12	11	2001	14	35	0.488	
20	8	1999	16	35	0.452		3	10	2003	13	35	-0.478	Employment Report
11	3	1999	17	5	0.436		11	3	1999	17	5	0.436	
5	3	1999	13	35	0.430	Employment Report	6	9	2002	8	5	0.425	
6	9	2002	8	5	0.425		2	6	2000	13	35	0.419	Employment Report
15	7	1998	9	35	-0.422		5	3	2004	13	35	0.415	Employment Report
2	6	2000	13	35	0.419	Employment Report	16	6	1999	13	35	0.401	CPI

Table 4.5.1.9. Largest Jumps and News for Euro Bund Futures.

Daily Jumps

DATE			$J_{1,t}$	DATE			$J_{1,t}(Z_{1,t})$
3	9	2004	0.42	3	9	2004	0.42
2	6	2000	0.28	2	6	2000	0.28
7	11	2003	0.24	7	11	2003	0.24
2	4	2004	0.22	2	4	2004	0.22
7	5	2004	0.20	7	5	2004	0.20
6	8	2004	0.19	6	8	2004	0.19
11	3	1999	0.19	11	3	1999	0.19
26	8	1998	0.19	26	8	1998	0.19
9	1	2004	0.15	9	1	2004	0.15
3	10	2003	0.13	3	10	2003	0.13
6	9	2002	0.11	6	9	2002	0.11
30	10	2003	0.11	30	10	2003	0.11

Intraday Jumps (Raw Returns)							Intraday Jumps (Standardised Returns)						
DATE			TIME		κ_k	NEWS	DATE			TIME		κ_k	NEWS
3	9	2004	14	35	-0.613	Employment Report	3	9	2004	14	35	-0.613	Employment Report
2	6	2000	14	35	0.574	Employment Report	2	6	2000	14	35	0.574	Employment Report
2	4	2004	15	35	-0.566		2	4	2004	15	35	-0.566	
9	10	1998	8	55	-0.530		7	5	2004	14	35	-0.494	Employment Report
7	5	2004	14	35	-0.494	Employment Report	7	11	2003	14	35	-0.484	Employment Report
7	11	2003	14	35	-0.484	Employment Report	26	8	1998	9	10	0.468	
26	8	1998	9	10	0.468		11	9	2001	15	45	0.442	Terrorist Attacks
11	9	2001	15	45	0.442	Terrorist Attacks	3	10	2003	14	35	-0.430	Employment Report
3	10	2003	14	35	-0.430	Employment Report	9	1	2004	14	35	0.429	Employment Report
9	1	2004	14	35	0.429	Employment Report	15	10	1999	14	35	-0.406	PPI
15	10	1999	14	35	-0.406	PPI	3	9	2004	14	30	0.406	Employment Report
3	9	2004	14	30	0.406	Employment Report	11	3	1999	17	50	0.405	
11	3	1999	17	50	0.405		6	8	2004	14	30	0.391	Employment Report
6	8	2004	14	30	0.391	Employment Report	8	10	1998	13	50	-0.379	
8	10	1998	13	50	-0.379		2	4	2004	15	30	-0.373	

Sequential Intraday Jumps

DATE			TIME		$\widetilde{\kappa}_k(Z_{1,t})$	NEWS	DATE			TIME		$\widetilde{\kappa}_k(U_{1,t})$	NEWS
3	9	2004	14	35	-0.613	Employment Report	3	9	2004	14	35	-0.613	Employment Report
2	6	2000	14	35	0.574	Employment Report	2	6	2000	14	35	0.574	Employment Report
2	4	2004	15	35	-0.566		2	4	2004	15	35	-0.566	
7	5	2004	14	35	-0.494	Employment Report	7	5	2004	14	35	-0.494	Employment Report
7	11	2003	14	35	-0.484	Employment Report	7	11	2003	14	35	-0.484	Employment Report
26	8	1998	9	10	0.468		3	10	2003	14	35	-0.430	Employment Report
3	10	2003	14	35	-0.430	Employment Report	9	1	2004	14	35	0.429	Employment Report
9	1	2004	14	35	0.429	Employment Report	15	10	1999	14	35	-0.406	PPI
15	10	1999	14	35	-0.406	PPI	11	3	1999	17	50	0.405	
11	3	1999	17	50	0.405		6	8	2004	14	30	0.391	Employment Report
6	8	2004	14	30	0.391	Employment Report	6	9	2002	14	35	-0.359	Employment Report
6	9	2002	14	35	-0.359	Employment Report	5	11	2004	14	30	-0.342	Employment Report
8	4	1999	18	20	0.356		4	2	2005	14	35	0.333	Employment Report
5	11	2004	14	30	-0.342	Employment Report	30	10	2003	14	35	-0.329	GDP Advance
5	12	2001	16	5	-0.337	ISM Services	10	11	1999	14	35	-0.327	Initial Claims, PPI

A number of findings emerge from the tables that are common across all nine futures markets considered. First, the statistically significant jump days in the top-right panel invariably correspond to the same days identified by the simple non-negative constraint in the top-left panel. This is entirely as expected, since increasing the statistical significance of the test from 0.5% to 0.001% should identify the larger jumps. Second, in the middle panel of the tables, the largest intraday jumps detected for raw returns match, in the vast majority of cases, those identified for standardised returns, implying that annihilating the intraday volatility pattern that is inherent in asset returns makes very little difference to the identification of these extreme intraday jumps. Third, in the bottom panel of the tables, the sequential intraday jump detection technique identifies the same five-minute intervals containing jumps between the $Z_{I,t}$ and $U_{I,t}$ versions of the test, with only very few dicrspancies between the two. Fourth, there is tremendous consistency between the jump measures in each of the three panels with the dates of daily jumps corresponding to the dates of intraday jumps, and the timings of intraday jumps corresponding to those of sequential intraday jumps in the lower two panels. This consistency is encouraging since it implies that, although the different methods detect differing numbers of intraday jumps, they all detect similar large jumps. Finally, the majority of these large jumps coincide with US macroeconomic news announcements, showing some violent price movements in response to macroeconomic news but, interestingly, the strength of reactions to the same news is different across markets. As reported in numerous previous studies, the Employment Report containing Non-Farm Payrolls and the Unemployment Rate (amongst other information) is the most important announcement driving price reactions, which are classified as jumps in this work. The remainder of this section highlights some of the more interesting points relating to the individual markets.

For the EUR-USD futures in Table 4.5.1.1 the three largest measures of jump variation are 1.84, 0.98 and 0.66, which are vastly larger than the sample average jump variation of 0.113 for significant jumps, as shown in Table 4.4.4.1. Jump variation falls to 0.31 for the twelvth largest jump, which remains much larger than the average. The top three EUR-USD jumps and six of the top twelve occur in 2004, confirming the earlier visual inspection of the plots in Figure 4.4.4.1, and these may be related to US economic performance and business cycle dynamics. Intraday jumps are very similar between those identified by raw returns and standardised returns in the middle panel of Table 4.5.1.1 and most correspond to macroeconomic news announcements, with the Employment Report being particularly prominent and Trade Balance, GDP Advance, Federal Open Market Committee (FOMC) interest rate decisions and Consumer Confidence announcements also being identified. This suggests that many jumps are related to information related to US macroeconomic conditions and later sections aim to provide a more detailed and systematic investigation of these relationships. Finally, intraday jumps identified by the sequential method in the lower panel of Table 4.5.1.1 show almost identical jumps between the $Z_{I,t}$ and $U_{I,t}$ versions of the test and between these jumps and the intraday jumps of the middle panel.

The consistency of jump detection between jump measures is confirmed in Table 4.5.1.2 for GBP-USD futures, although the largest jumps are found to occur at different times than those for EUR-USD. Greater proportions of the largest intraday jumps identified coincide with US macroeconomic news, and the Employment Report in particular. It is interesting that these are not always the same data releases causing the largest jumps in EUR-USD, showing that reaction to news is heterogeneous across markets. GBP-USD also reveals lower measures of jump variation and intraday jumps as compared to EUR-USD. Jumps in JPY-USD are closer in magnitude to those for EUR-USD, but few of the jump dates match those of EUR-USD or GBP-USD. JPY-USD futures confirm the consistency of jump detection for these large jumps throughout the panels of Table 4.5.1.3 and US macroeconomic news again shows an important role with the Employment Report dominating, supported by Trade Balance and Chicago PMI releases.

Table 4.5.1.4 shows the largest jumps identified for the S&P 500 E-Mini futures contract, the first of the equity index futures markets considered. In addition to confirming the consistency of jump detection, the table shows enormous jumps compared to the foreign exchange futures, which feature on different dates. This is not to say that jump detection is inconsistent across markets, but simply that the largest jumps do not always occur on the same days. Macroeconomic news is an important contributor to the jumps, although some of the large intraday jumps cannot be attributed to the macroeconomic news releases in this sample. The Employment Report maintains its significance for this market, however, inter-meeting interest rate changes by the FOMC supercede it by causing larger jumps. It is interesting that these unscheduled announcements also cause multiple, consecutive, large intraday jumps, implying price reaction and volatility beyond five minutes following the announcements.

Jump variations and intraday jumps are noticeably high for FTSE 100 futures in Table 4.5.1.5, confirming the evidence in section 4.4.4 that shows equity futures to exhibit larger average jumps than foreign exchange or interest rate futures markets. The timings of the jumps in this market are different from the S&P 500 E-Mini and foreign exchange futures, which may be explained by the FTSE 100 futures market being open at different trading hours than the US based markets. Fewer of the largest intraday jumps correspond to US macroeconomic news than in the previous markets. However, some of the very largest jumps followed terrorist attacks in New York and London, whereas the next largest jumps correspond more frequently to US news. Most UK macroeconomic announcements are made at 8.30 or 10.00 in London, but with very few of the largest intraday jumps occurring at these times and only 26 of all the FTSE 100 futures intraday jumps (raw returns using α=0.001) occurring at these times, not necessarily on UK news announcement days, there is little evidence that UK macroeconomic news is more important for driving intraday jumps.[25] This is the first market thus far to display minor discrepancies in the measurement of the largest intraday jumps across methods. Standardising returns does not identify four intraday jumps that raw returns do identify, whilst the sequential method does not identify approximately half of those identified by the standardised returns. The importance of this result is that both standardising and the sequential method do not catagorise some large returns as jumps. The importance of US macroeconomic news remains, with some intraday jumps corresponding to announcements.

The largest jumps for the DJ Euro Stoxx 50 futures are presented in Table 4.5.1.6, which shows them to be particularly large and similar in size to those for the S&P 500 E-Mini contract. The largest jump is caused by the terrorist attacks in New York, although the $U_{1,t}$ test statistic does not recognise this day as containing a jump. Very few of the jumps correspond to those of the S&P 500 E-Mini or FTSE 100 futures, confirming that timings and sizes of the largest jumps vary across international futures markets. In support of the findings for the FTSE 100 futures, US

[25] There is even less correspondence of jumps with the regular timings of Eurozone, German and French news announcements, supporting the assertion that US news dominates in this context. Of course, an empirical study of the impacts of news from other countries in causing jumps in these markets is required to test this suggestion, but, unfortunately non-US macroeconomic data is not available for this study and this interesting extension is left for future work.

macroeconomic news generates some sizeable jumps, but not all of the large intraday jumps. Casual inspection reveals a maximum of only 41 incidences of intraday jumps at times of European macroeconomic announcements (including non-announcement days), compared to 115 for US news. Although standardisation eliminates a few of the intraday jumps found for raw returns, it is encouraging to find strong consistency between the sequential intraday jumps and those found using standardised returns.

Turning to the interest rate futures markets, jumps in the US 10-Year Treasury Bond futures market are smaller than those of the equity futures markets and similar in size to those of the forign exchange market, as shown in Table 4.5.1.7. There is consistency in jump detection across the various methods and only a small number of jumps match those of the foreign exhange and equity markets, showing further evidence of heterogeneous behaviour across international markets. The lower panels of the table show that every intraday jump corresponds to US maroeconomic news and to the Employment Report, FOMC interest rate decisions, and GDP Advance in particular. It is interesting, however, that the magnitude of such dramatic jumps occurring around macroeconomic news releases is not identical across markets, showing that reactions to news are different across asset classes and geographical regions.

The UK Gilt futures market is represented in Table 4.5.1.8 and shows smaller jump variations relative to the markets discussed above. Despite this lower daily jump variation, intraday jumps remain high and are similar in size to the US 10-Year T-Bond and foreign exchange futures markets. Again, there is strong consistency between jump measures and some correspondence of these intraday jumps with US Employment Report news, a small number of which match the jumps found in the foreign exchange and US 10-Year T-Bond markets. There is one large jump in response to an interest rate decision by the Monetary Policy Committee (MPC) of the Bank of England, the only UK news item included in this study, but this is not recognised as a jump day by the sequential intraday jump detection method.[26]

Finally, Table 4.5.1.9 displays the largest jumps for the Euro Bund futures. Jump variation is noticeably smaller for Bund futures than all other markets and the largest intraday jumps are also relatively small in comparison. In support of the

[26] As with the other European and UK markets considered and, based on casual inspection of the data, news regarding the performance of these economies is not thought to be important drivers of intraday jumps, although this assertion requires more robust treatment for corroboration.

findings for the other markets, there is strong consistency in the largest jumps identified by different detection procedures and the importance of US macroeconomic news, and the Employment Report in particular, in causing many of the intraday jumps. Contrary to the foreign exchange and equity index futures, the timing of some of the largest jumps in interest rate futures are common across the Euro Bund, US 10-Year T-Bond and UK Gilt futures, showing some similarities in reactions to US macroeconomic news.

In brief summary, this section has provided details of the largest jumps occurring in each futures market. It is encouraging that there is strong consistency between the largest jumps identified by alternative jump detection methods and it is interesting to note that, often, the timings of the largest jumps are not uniform across all markets, showing heterogeneous reactions to news aross asset classes and geographical locations. There is a strong influence from the announcement of the US Employment Report in causing the majority of the largest intraday jumps. A more systematic and detailed examination of these relationships is performed in the following sections.

4.5.2 Intraday Jumps and News Dummy Variables

Given the evidence in the previous section for the influence of US macroeconomic news announcements on intraday jumps, this section provides an investigation of more systematic relationships. For an individual macroeconomic indicator, δ, the absolute value of intraday jumps, detected for raw returns using the method of Andersen, Bollerslev and Dobrev (2007), is regressed on a dummy variable, D_δ, taking the value unity if the five-minute interval, k, immediately follows an announcement of information relating to release δ. The equation is specified as:

$$|\kappa_k| = \omega_\delta + \beta_\delta D_{\delta,k} + \varepsilon_{\delta,k} \,. \tag{4.41}$$

The parameter β_δ measures the contribution of the announcement of news regarding release δ to the average absolute value of intraday jumps with inference based on Newey and West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors.[27] If US macroeconomic news announcements demonstrate a significant effect on the occurrence and magnitude of intraday jumps, as is suggested by the evidence of the previous section, then β_δ is expected to be positive.

Tables 4.5.2.1 to 4.5.2.9 display the results of these regressions performed for all US macroeconomic news indicators in the sample, and for intraday jumps detected at significance levels of α=0.01, 0.001 and 0.0001, and for each of the nine futures contracts included in this study. In addition to reporting the coefficient estimates and inference for β_δ, the tables also include the total number of intraday jumps in each regression, the total number of announcements for each news category (N($D_{\delta,k}$)) and the number of coincidences of intraday jumps and news announcements (N($D_{\delta,k}$, κ_k)). The tables also show the results of a single regression combining all news dummies into a single variable (All News).

A number of general findings emerge from inspection of the tables. First, the number of jumps in each market, even at the most accommodating significance level, is less than the total number of news announcements meaning that many news announcements do not cause jumps. This is entirely expected, since only surprises should move prices significantly, relative to other trading activity on a particular announcement day. Second, the number of occurrences of jumps which coincide with all news announcements is less than the total number of jumps, indicating that not all jumps can be explained by the arrival of US macroeconomic information.[28] The third general finding of the tables shows that as the significance level of the jump detection test is reduced, fewer jumps are identified, fewer instances of jumps and news announcements (all news) coinciding are found, yet the number of these interactions as a proportion of the total number of jumps increases markedly.

[27] This test matches intraday jumps to the five-minute intervals containing news announcements. As shown in the previous section, intraday jumps sometimes occur immediately prior to and following the announcement, such that an announcement window would coincide with more intraday jumps. In the interests of conserving space, this is left for future work.

[28] Of course, it is possible that macroeconomic news from other countries may cause jumps in financial markets. However, casual inspection of the data shows that this additional data is unlikely to make a large contribution to the explanation of jumps. Although the information set here is not rich enough to provide a definitive answer, we may speculate that private information, speeches, rumours, liquidity, trading volume or other types of economic or geo-political news may also contribute to causing price jumps. The theoretical model of equation (4.1) may also suggest that jumps are an inherent part of the price process and therefore may not necessarily require explicit explanations for their occurrence.

Table 4.5.2.1. Intraday Jumps and News Dummy Variables for EUR-USD Futures (Raw Returns).

α		0.01 No. Jumps: 997		0.001 No. Jumps: 571		0.0001 No. Jumps: 357	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,840	207	**0.076****	166	**0.069****	127	**0.074****
Business Inventories	84	8	**0.045+**	6	**0.049***	6	0.015
Chicago PMI	82	7	0.015	6	0.003	4	-0.002
Construction Spending	88	10	**0.048***	9	0.012	7	-0.028
Consumer Confidence	89	19	0.012	16	-0.010	9	0.001
CPI	88	10	**0.052***	8	0.033	7	0.008
Current Account	25	2	**0.042****	2	0.006	2	-0.029
Employment Cost Index	30	7	**0.066+**	4	0.046	3	0.043
Existing Home Sales	89	6	-0.021	5	-0.049	4	-0.068
Factory Orders	86	5	-0.017	3	-0.019	3	-0.053
GDP Advance	30	12	**0.087***	9	0.068	6	**0.096+**
GDP Prel	27	2	**0.063****	2	**0.027+**	2	-0.007
Housing Starts	89	6	-0.026	3	-0.039	2	-0.074
Initial Claims	378	41	0.015	26	-0.001	18	-0.011
ISM Manufacturing	88	12	**0.045***	11	0.010	9	-0.030
Leading Indicators	90	3	-0.080	1	-0.076	1	-0.111
Mich Sentiment Prel	77	3	-0.047	2	-0.039	1	-0.073
Mich Sentiment Rev	75	1	-0.103	1	-0.139		
New Home Sales	88	8	0.039	7	0.009	4	0.037
NY Empire State Index	36	7	**0.037+**	6	0.014	5	0.000
Non-Farm Payrolls	81	40	**0.220****	38	**0.199****	34	**0.196****
Personal Income	80	4	-0.011	2	**0.017****	1	-0.022
Personal Spending	80	4	-0.011	2	**0.017****	1	-0.022
PPI	83	18	**0.030+**	15	0.009	12	0.000
Productivity Prel	30	5	0.000	4	-0.028	1	**0.018***
Productivity Rev	30	4	-0.023	1	-0.038	1	-0.073
Retail Sales	87	20	0.012	16	-0.011	13	-0.028
Trade Balance	87	20	**0.061***	18	0.034	13	0.030
Unemployment Rate	81	40	**0.220****	38	**0.199****	34	**0.196****
FOMC	63	14	**0.070***	12	**0.055+**	10	0.039

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in EUR-USD futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.2. Intraday Jumps and News Dummy Variables for GBP-USD Futures (Raw Returns).

α		0.01 No. Jumps: 1,067		0.001 No. Jumps: 592		0.0001 No. Jumps: 350	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,950	148	**0.071****	102	**0.084****	72	**0.102****
Business Inventories	90	6	0.022	3	**0.055+**	2	0.041
Chicago PMI	87	5	**0.036***	3	0.011	3	-0.011
Construction Spending	94	7	-0.008	5	-0.020	3	-0.036
Consumer Confidence	95	10	**0.033***	7	0.021	6	0.008
CPI	94	8	**0.057***	7	**0.048***	3	**0.067+**
Current Account	25	3	-0.020	2	-0.026	2	-0.048
Employment Cost Index	32	3	**0.050+**	3	0.026	2	**0.038+**
Existing Home Sales	94	3	-0.027	2	-0.047	1	-0.084
Factory Orders	91	3	0.013	2	0.008	2	-0.014
GDP Advance	32	7	**0.103***	7	**0.080+**	5	**0.108***
Housing Starts	95	4	-0.037	1	-0.029		
Initial Claims	400	22	**0.047****	16	**0.045****	10	**0.027+**
ISM Manufacturing	94	8	-0.013	6	-0.029	3	-0.036
Leading Indicators	97	2	-0.046	1	-0.024		
Mich Sentiment Prel	82	3	-0.029	1	-0.045		
New Home Sales	93	5	0.021	3	0.018	1	**0.052****
NY Empire State Index	36	5	0.024	3	**0.048+**	2	**0.059+**
Non-Farm Payrolls	85	33	**0.176****	27	**0.185****	24	**0.195****
Personal Income	84	3	0.017	2	0.007	1	**0.008+**
Personal Spending	84	3	0.017	2	0.007	1	**0.008+**
PPI	89	10	**0.037***	6	**0.048***	5	**0.040***
Productivity Prel	32	1	-0.016				
Productivity Rev	32	2	**0.025***				
Retail Sales	93	14	0.011	8	0.020	3	0.022
Trade Balance	92	19	**0.062****	14	**0.056***	11	**0.062***
Unemployment Rate	85	33	**0.176****	27	**0.185****	24	**0.195****
FOMC	66	10	**0.042+**	7	0.035	4	0.012

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in GBP-USD futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.3. Intraday Jumps and News Dummy Variables for JPY-USD Futures (Raw Returns).

α		0.01 No. Jumps: 948		0.001 No. Jumps: 522		0.0001 No. Jumps: 300	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,951	112	**0.057****	75	**0.066****	52	**0.076****
Business Inventories	90	2	**0.045***	1	**0.047****	1	**0.011+**
Capacity Utilization	88	1	0.003				
Chicago PMI	87	5	0.136	3	0.222	2	**0.366+**
Construction Spending	94	6	-0.039	3	-0.059		
Consumer Confidence	95	8	-0.014	6	-0.043	3	-0.066
CPI	94	5	0.003	3	-0.017	1	**0.011+**
Current Account	25	1	**0.024****	1	-0.010	1	-0.046
Employment Cost Index	32	4	-0.001	2	0.011	2	-0.025
Existing Home Sales	94	2	-0.033	2	-0.068		
Factory Orders	91	1	**0.023****	1	-0.011		
GDP Advance	32	7	-0.001	4	0.000	4	-0.036
GDP Final	31	1	-0.096				
GDP Prel	29	1	**0.055****				
Housing Starts	95	3	-0.017	1	-0.048		
Industrial Production	88	1	0.003				
Initial Claims	401	19	-0.001	12	-0.010	7	-0.032
ISM Manufacturing	94	6	-0.021	4	-0.040		
Mich Sentiment Prel	82	2	0.001				
Mich Sentiment Rev	80	1	-0.081				
New Home Sales	93	5	**0.047+**	3	**0.063+**	3	0.028
NY Empire State Index	36	1	**0.028****	1	-0.006	1	-0.042
Non-Farm Payrolls	85	29	**0.153****	25	**0.150****	21	0.149
Personal Income	84	5	-0.030	1	**0.017***	1	-0.019
Personal Spending	84	5	-0.030	1	**0.017***	1	-0.019
PPI	89	5	0.017	3	0.014	1	**0.098****
Productivity Prel	32	2	0.098	2	0.064	1	**0.151****
Retail Sales	93	8	-0.019	6	-0.044	3	-0.064
Trade Balance	93	13	**0.068+**	10	0.059	7	0.044
Unemployment Rate	85	29	**0.153****	25	**0.150****	21	**0.149****
FOMC	66	6	**0.029+**	5	-0.006	5	-0.043

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in JPY-USD futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.4. Intraday Jumps and News Dummy Variables for S&P 500 E-Mini Futures (Raw Returns).

A		0.01 No. Jumps: 697		0.001 No. Jumps: 365		0.0001 No. Jumps: 190	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	2,135	151	**0.198****	112	**0.217****	80	**0.177****
Business Inventories	95	9	0.093	8	-0.008	8	-0.148
Chicago PMI	96	13	-0.008	8	-0.063	4	-0.228
Construction Spending	94	15	0.027	9	-0.003	3	-0.032
Consumer Confidence	96	14	**0.106+**	11	0.066	7	0.040
CPI	96	16	-0.002	12	-0.085	11	-0.212
Current Account	25	1	**0.237****	1	**0.147****		
Employment Cost Index	32	5	**0.236+**	4	**0.230+**	4	0.096
Existing Home Sales	96	2	-0.146	1	-0.122	1	-0.257
Factory Orders	95	6	-0.021	5	-0.071	1	-0.394
GDP Advance	32	6	**0.386***	5	**0.394***	4	**0.381+**
GDP Prel	32	1	0.166	1	**0.075****	1	-0.059
Housing Starts	96	5	-0.086	3	-0.151	2	-0.236
Initial Claims	413	16	**0.090+**	11	0.080	9	-0.068
ISM Manufacturing	94	17	0.042	10	0.040	4	0.046
Leading Indicators	97	5	0.071	4	-0.038	2	-0.172
Mich Sentiment Prel	93	3	-0.040	2	-0.133	1	-0.131
Mich Sentiment Rev	95	5	0.034	3	0.040	3	-0.095
New Home Sales	95	6	-0.099	2	-0.040	1	-0.279
NY Empire State Index	36	2	-0.159	2	-0.251	2	-0.387
Non-Farm Payrolls	93	29	**0.289****	27	**0.237****	22	**0.151+**
Personal Income	93	1	-0.262				
Personal Spending	93	1	-0.262				
PPI	95	10	0.059	7	0.006	4	-0.067
Productivity Prel	31	5	-0.012	5	-0.105	4	-0.261
Productivity Rev	32	2	0.004	1	**0.099****		
Retail Sales	95	13	**0.054+**	10	-0.012	6	-0.121
Trade Balance	96	2	-0.114				
Unemployment Rate	93	29	**0.289****	27	**0.237****	22	**0.151+**
FOMC	67	15	**0.760***	10	**1.100****	10	**0.988***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in S&P 500 E-Mini futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.5. Intraday Jumps and News Dummy Variables for FTSE 100 Futures (Raw Returns).

α		0.01 No. Jumps: 835		0.001 No. Jumps: 447		0.0001 No. Jumps: 264	
	N($D_{\delta,k}$)	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ
All News	2,049	95	**0.157****	67	**0.164****	49	**0.126****
Business Inventories	92	3	-0.005				
Chicago PMI	91	4	0.084	3	**0.132***	2	-0.013
Construction Spending	88	7	**0.106***	4	**0.112+**	3	0.058
Consumer Confidence	93	12	**0.186****	11	**0.141****	8	0.054
CPI	95	9	-0.009	4	0.046	2	**0.136***
Employment Cost Index	32	6	**0.211***	4	**0.259***	2	**0.415****
Existing Home Sales	92	2	-0.040	2	-0.100	2	-0.170
Factory Orders	95	4	0.118	2	**0.069***	2	-0.001
GDP Advance	32	8	0.169	5	**0.208+**	4	**0.231***
GDP Prel	32	2	**0.093****	2	0.034	2	-0.037
Housing Starts	96	1	-0.017	1	-0.076		
Initial Claims	406	16	**0.124***	12	**0.124***	8	**0.142***
ISM Manufacturing	87	7	**0.106***	4	**0.112+**	3	0.058
Leading Indicators	93	3	0.024	2	**0.038***	1	-0.057
Mich Sentiment Prel	92	3	0.209	2	0.274	1	**0.618****
Mich Sentiment Rev	93	4	0.188	3	**0.264+**	2	0.002
NY Empire State Index	37	1	-0.235				
Non-Farm Payrolls	94	23	**0.214****	18	**0.203****	15	**0.188***
Personal Income	89	1	**0.076****				
Personal Spending	89	1	**0.076****				
PPI	93	5	0.070	4	-0.071	2	-0.139
Productivity Prel	32	4	0.048	3	-0.003	2	0.014
Retail Sales	94	7	**0.130+**	4	0.113	3	0.131
Trade Balance	95	1	**0.294****	1	**0.235****	1	0.165
Unemployment Rate	94	23	**0.214****	18	**0.203****	15	**0.188***
BOE	95	3	**0.312****	3	**0.253****	2	**0.210****
ECB	115	1	**0.177****	1	**0.118****	1	**0.048***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in FTSE 100 futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, κ_k) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.6. Intraday Jumps and News Dummy Variables for DJ Euro Stoxx 50 Futures (Raw Returns).

α		0.01 No. Jumps: 859		0.001 No. Jumps: 463		0.0001 No. Jumps: 279	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,969	163	**0.220****	115	**0.247****	87	**0.203****
Business Inventories	89	9	**0.206+**	6	0.292	5	**0.313***
Capacity Utilization	89	1	-0.162				
Chicago PMI	86	14	0.090	8	**0.130+**	6	-0.027
Construction Spending	84	13	**0.197***	9	0.100	6	0.096
Consumer Confidence	88	20	**0.181***	15	**0.187***	10	0.016
CPI	90	14	0.059	8	**0.135+**	6	**0.148***
Current Account	25	1	-0.030				
Employment Cost Index	30	6	0.137	5	0.104	3	**0.197+**
Existing Home Sales	88	3	0.020	1	**0.227****	1	**0.146****
Factory Orders	89	7	**0.153+**	4	0.169	3	0.088
GDP Advance	30	14	**0.243****	11	**0.256****	7	**0.272***
GDP Prel	30	3	0.040	1	**0.465****	1	**0.384****
Housing Starts	90	6	-0.037	3	0.004	2	0.060
Industrial Production	89	1	-0.162				
Initial Claims	382	22	0.068	16	0.060	12	-0.022
ISM Manufacturing	83	16	**0.224****	12	**0.137+**	9	0.119
Leading Indicators	89	3	0.053	2	0.019	2	-0.063
Mich Sentiment Prel	89	6	0.171	3	0.294	2	-0.092
Mich Sentiment Rev	89	6	0.179	3	0.272	1	**1.146****
New Home Sales	90	5	-0.157	1	-0.110	1	-0.192
NY Empire State Index	37	2	-0.178	1	-0.215		
Non-Farm Payrolls	89	29	**0.325****	25	**0.271****	24	**0.212***
Personal Income	88	2	-0.003	2	-0.096		
Personal Spending	88	2	-0.003	2	-0.096		
PPI	88	10	**0.174+**	6	0.200	4	**0.362***
Productivity Prel	29	6	**0.105+**	6	0.012	4	-0.011
Productivity Rev	30	2	0.041	1	**0.100****		
Retail Sales	89	14	0.059	11	0.026	9	-0.089
Trade Balance	90	5	-0.074	2	-0.135	2	-0.217
Unemployment Rate	89	29	**0.325****	25	**0.271****	24	**0.212***
FOMC	3	2	**0.452***	2	**0.360+**	2	0.279
BOE	91	1	-0.042	1	-0.135		
ECB	116	2	**0.641****	2	**0.549****	2	**0.469****

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in DJ Euro Stoxx 50 futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.7. Intraday Jumps and News Dummy Variables for US 10-Year T-Bond Futures (Raw Returns).

α		0.01 No. Jumps: 920		0.001 No. Jumps: 596		0.0001 No. Jumps: 419	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,903	342	**0.083****	271	**0.085****	225	**0.073****
Business Inventories	87	16	**0.076***	15	0.045	13	0.037
Capacity Utilization	87	7	-0.028	7	-0.060	6	-0.087
Chicago PMI	86	18	0.004	14	-0.003	10	-0.024
Construction Spending	93	36	**0.023+**	26	**0.026+**	21	-0.012
Consumer Confidence	95	24	0.007	18	-0.016	12	-0.024
CPI	94	34	**0.047****	28	**0.036+**	22	0.029
Current Account	25	2	0.049	2	0.018	2	-0.011
Employment Cost Index	32	9	**0.181****	8	**0.167****	8	**0.139****
Existing Home Sales	94	9	-0.040	5	-0.057	3	-0.113
Factory Orders	90	11	-0.049	9	-0.069	7	-0.092
GDP Advance	32	15	**0.112****	14	**0.086****	12	**0.060+**
GDP Final	31	3	-0.073	1	-0.053	1	-0.082
GDP Prel	29	5	-0.051	2	-0.036	2	-0.065
Housing Starts	95	16	-0.015	11	-0.025	9	-0.041
Industrial Production	87	7	-0.028	7	-0.060	6	-0.087
Initial Claims	393	61	0.008	44	-0.005	36	-0.024
ISM Manufacturing	92	37	**0.036***	28	**0.036+**	23	0.001
Leading Indicators	96	7	-0.010	4	0.016	3	0.020
Mich Sentiment Prel	77	8	-0.026	6	-0.036	3	-0.076
Mich Sentiment Rev	73	3	**0.069****	3	**0.039***	2	**0.036****
New Home Sales	88	16	-0.017	10	0.000	7	-0.015
NY Empire State Index	36	11	0.012	10	-0.005	8	-0.018
Non-Farm Payrolls	80	50	**0.256****	43	**0.262****	40	**0.255****
Personal Income	81	6	0.019	5	0.003	5	-0.026
Personal Spending	81	6	0.019	5	0.003	5	-0.026
PPI	84	22	0.012	17	-0.018	17	-0.049
Productivity Prel	32	5	0.028	4	0.010	3	0.028
Productivity Rev	32	2	-0.061	2	-0.091	1	-0.083
Retail Sales	91	41	**0.031***	34	0.010	31	-0.014
Trade Balance	90	5	-0.011	4	-0.024	4	-0.054
Unemployment Rate	80	50	**0.256****	43	**0.262****	40	**0.255****
FOMC	66	28	**0.106****	24	**0.087****	22	**0.059+**

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in US 10-Year T-Bond futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.8. Intraday Jumps and News Dummy Variables for UK Gilt Futures (Raw Returns).

α		0.01 No. Jumps: 1,435		0.001 No. Jumps: 880		0.0001 No. Jumps: 581	
	N($D_{\delta,k}$)	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ
All News	2,034	184	**0.040****	140	**0.043****	113	**0.044****
Business Inventories	92	7	**0.074****	5	**0.079****	4	**0.079****
Capacity Utilization	94	4	-0.047	1	-0.064		
Chicago PMI	90	11	0.003	9	-0.007	8	-0.016
Construction Spending	87	14	0.014	8	0.021	6	0.023
Consumer Confidence	91	13	-0.008	9	-0.011	5	0.016
CPI	95	19	0.018	13	0.015	10	0.012
Current Account	25	2	-0.049				
Employment Cost Index	32	8	**0.078****	7	**0.076****	6	**0.072***
Existing Home Sales	90	1	-0.054				
Factory Orders	96	4	-0.011	3	-0.026	2	-0.012
GDP Advance	32	11	**0.067****	10	**0.056***	8	0.054
GDP Final	31	2	0.003	1	-0.042	1	-0.060
Housing Starts	96	6	0.032	2	0.105	2	0.087
Industrial Production	94	4	-0.047	1	-0.064		
Initial Claims	401	22	**0.031***	14	**0.048***	12	0.042
ISM Manufacturing	86	17	**0.023+**	11	**0.028+**	9	**0.025+**
Leading Indicators	94	4	0.020	4	0.000	4	-0.019
Mich Sentiment Prel	91	9	-0.010	7	-0.023	3	-0.016
Mich Sentiment Rev	92	2	-0.021	1	-0.010	1	-0.029
New Home Sales	88	2	-0.042	1	-0.046	1	-0.065
NY Empire State Index	37	5	0.036	4	0.037	2	**0.096+**
Non-Farm Payrolls	93	37	**0.127****	34	**0.123****	32	**0.116****
Personal Income	87	2	-0.015	1	-0.048	1	-0.066
Personal Spending	87	2	-0.015	1	-0.048	1	-0.066
PPI	92	18	0.000	13	-0.004	9	-0.010
Productivity Prel	31	3	**0.127****	3	**0.107****	3	**0.089****
Productivity Rev	32	1	**0.071****	1	**0.051****	1	**0.033****
Retail Sales	93	24	0.008	19	0.001	15	-0.012
Trade Balance	93	3	-0.021	2	-0.020	2	-0.038
Unemployment Rate	93	37	**0.127****	34	**0.123****	32	**0.116****
BOE	94	11	**0.055***	10	**0.042+**	8	0.028

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in UK Gilt futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, κ_k) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.9. Intraday Jumps and News Dummy Variables for Euro Bund Futures (Raw Returns).

α		0.01 No. Jumps: 1,316		0.001 No. Jumps: 790		0.0001 No. Jumps: 534	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	2,095	266	**0.032****	206	**0.029****	163	**0.031****
Business Inventories	95	12	**0.054***	9	**0.058***	7	**0.058+**
Capacity Utilization	95	8	-0.013	5	-0.032	4	-0.036
Chicago PMI	89	15	0.008	12	-0.007	10	-0.012
Construction Spending	90	25	**0.016+**	18	0.011	14	0.009
Consumer Confidence	93	16	0.004	10	0.010	8	0.016
CPI	96	28	-0.001	18	-0.008	14	-0.019
Current Account	25	2	-0.020	2	-0.040	2	-0.055
Employment Cost Index	32	10	**0.074****	9	**0.062****	9	**0.047****
Existing Home Sales	93	4	-0.030	1	**0.010****	1	-0.005
Factory Orders	95	11	-0.023	9	-0.042	7	-0.055
GDP Advance	32	14	**0.064****	14	**0.044****	14	**0.029***
GDP Final	32	3	-0.047	2	-0.063	1	-0.065
GDP Prel	32	3	-0.036	1	-0.052		
Housing Starts	96	6	-0.004	4	-0.009	4	-0.024
Industrial Production	95	8	-0.013	5	-0.032	4	-0.036
Initial Claims	405	41	**0.014+**	30	0.010	23	0.002
ISM Manufacturing	90	28	**0.026***	21	**0.022+**	17	**0.021+**
Leading Indicators	95	6	0.007	4	-0.023	1	**0.051****
Mich Sentiment Prel	94	12	-0.003	12	-0.024	6	-0.008
Mich Sentiment Rev	93	5	**0.042+**	3	**0.063***	3	**0.048***
New Home Sales	93	10	-0.017	7	-0.035	5	-0.037
NY Empire State Index	37	7	-0.018	6	-0.032	4	-0.036
Non-Farm Payrolls	95	48	**0.103****	44	**0.094****	35	**0.106****
Personal Income	93	4	0.007	3	0.002	1	-0.010
Personal Spending	93	4	0.007	3	0.002	1	-0.010
PPI	94	19	0.025	15	0.020	11	0.028
Productivity Prel	31	5	**0.049***	4	**0.054****	4	**0.039****
Productivity Rev	32	1	-0.033				
Retail Sales	95	29	0.011	24	-0.004	20	-0.011
Trade Balance	96	6	-0.012	3	0.004	3	-0.011
Unemployment Rate	95	48	**0.103****	44	**0.094****	35	**0.106****
FOMC	7	2	-0.043	1	-0.059		
BOE	97	2	**0.055****	1	**0.035****	1	**0.020****
ECB	118	6	**0.048***	5	**0.047****	5	**0.032***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in Euro Bund futures returns. Intraday jumps are detected according to equation (4.36) using raw returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

This suggests that, as the jump test becomes more stringent, the larger jumps are retained and proportionately more of these jumps correspond to the announcement of US macroeconomic news. These proportions vary across markets, ranging from 17.3% for JPY-USD futures to 53.7% for US 10-Year T-Bond futures (for α=0.0001), implying that the influence of news arrival varies across markets. Finally, for all news combined, β_δ is statistically significantly positive at the 1% level for all markets and regardless of the statistical significance level of the intraday jump test. This shows that the arrival of public information, in the form of US macroeconomic news, increases the absolute size of intraday jumps significantly. The extent of this effect varies across markets as the following review details.

Table 4.5.2.1 shows the estimation results for EUR-USD futures. The first row of the table for 'All News' shows, as noted above, that the number of coincidences of jumps and news (N($D_{\delta,k}$, κ_k)) falls as the statistical significance level of the jump test (α) decreases, however, the proportion of jump and news coincidences to total jumps rises from 20.8% to 29.1% and 35.6% for α=0.01, 0.001 and 0.0001 respectively. At the preferred significance level of 0.001, therefore, news announcements contribute almost 30% of all intraday jumps identified. β_δ for this regression is 0.069, which is statistically significantly greater than zero at the 1% level, and shows that macroeconomic announcements contribute an incremental 0.069 to the average absolute intraday jumps that do not coincide with any news announcements (ω_δ in equation (4.41)). In terms of economic significance, this represents an increment of 27.4% relative to ω_δ, showing that US macroeconomic news announcements contribute heavily to both the size and occurrence of intraday jumps. The results for the individual announcements show large numbers of incidences of jumps coinciding with news for Consumer Confidence, GDP Advance, Initial Claims, PPI, Retail Sales, Trade Balance and FOMC, but these lack statistically significant contributions. The Employment Report, containing most prominently Non-Farm Payrolls and the Unemployment Rate, however, shows that 46.9% of the announcements available in the EUR-USD sample relate to jumps, β_δ measures an increment of 0.199 to average non-announcement absolute jumps, representing on average, an additional contribution of 76.8% of this average following this announcement.

The results for GBP-USD in Table 4.5.2.2 show lower proportions of jumps being explained by US macroeconomic news announcements at 13.9%, 17.2% and

20.6%. Estimated values of β_δ, and the proportion of jumps caused by news, both rise as α falls and the jump test becomes more stringent, taking the values 0.071, 0.084 and 0.102, which are all statistically significantly greater than zero. At the preferred significance level of 0.001, news announcements thus contribute an average 0.084 in addition to the average absolute intraday jumps that do not coincide with news announcements of 0.186 (representing an increase of 45.1% on this average when announcements occur). These figures show that although news announcements do not cause such a large proportion of intraday jumps as for EUR-USD futures, those news announcements that do relate to jumps contribute more heavily to the magnitude of absolute jumps in economic terms, and this is partly due to smaller absolute intraday jumps for this market on average. For individual announcements, $N(D_{\delta,k}, \kappa_k)$ values are smaller for GBP-USD than EUR-USD, even though the total number of jumps is larger in this market. The more prominent announcements in terms of $N(D_{\delta,k}, \kappa_k)$ and the statistical significance of β_δ are CPI, GDP Advance, Initial Claims, PPI and Trade Balance, but in confirmation of the previous results for EUR-GBP, these are dwarfed by the effect of the Employment Report. Of the 85 announcements available, 27 cause intraday jumps which are detected with α=0.001 and these contribute 0.185 to average absolute intraday jumps not coincident with the release of the Employment Report. This represents an incremental 96.3% of this average showing that the average absolute intraday jump nearly doubles when jumps coincide with announcements of the Employment Report.

For the JPY-USD futures in Table 4.5.2.3, $N(D_{\delta,k}, \kappa_k)$, proportions and estimates of β_δ are lower than for GBP-USD. Of the 522 jumps, 75 relate to news announcements (according to α=0.001) and the average of these absolute jumps is 0.066 higher than for jumps not coinciding with news, representing an incremental 26.7% of this average. These are smaller than GBP-USD, but similar in magnitude to EUR-USD futures. Consumer Confidence, GDP Advance, Initial Claims, Retail Sales, Trade Balance and FOMC indicators provide the largest $N(D_{\delta,k}, \kappa_k)$, but the associated estimates of β_δ are not significantly greater than zero. The Employment Report, as for the previous two foreign exchange futures contracts, is dominant and is the only individual announcement for JPY-USD to provide statistically significant estimates of β_δ along with sufficient values of $N(D_{\delta,k}, \kappa_k)$. Almost 30% of all Employment Report releases generate intraday jumps and, on average, these add 0.150 to the average absolute intraday jumps not coinciding with the announcement of this indicator. The economic significance of this news is further emphasised for this market as this increment represents a 60.2% increase in this average due to this indicator.

Turning to the results for the equity index futures, Table 4.5.2.4 shows the regression output for the S&P 500 E-Mini futures. For all news combined, the extent of N($D_{\delta,k}$, κ_k) as a proportion of the total number of jumps is large, and similar in scale to those for EUR-USD futures, and rises as the jump test becomes more stringent showing that many of the larger jumps that are retained are related to macroeconomic news announcements. The corresponding estimates of β_δ are much larger than for the foreign exchange futures, at 0.198, 0.217 and 0.177 for the three absolute intraday jump series for various levels of α, showing large increases in absolute jump size in response to macroeconomic information releases. Not only are the magnitude and statistical significance of these coefficients remarkable, but their scale relative to average absolute non-announcement jumps is also noteworthy (45.1% for α=0.001). Together, these results provide evidence of the importance of US macroeconomic news announcements in causing intraday jumps in this market. The individual announcements causing large N($D_{\delta,k}$, κ_k) are Consumer Confidence, CPI, Initial Claims, ISM Index and Retail Sales, but these do not generate statistically significant increases in average absolute intraday jumps. In addition, GDP Advance, Employment Report and FOMC announcements provide statistically significant coefficient estimates. For α=0.001, these contribute an incremental 0.394, 0.237 and 1.100 to average absolute jumps, which are significant at the 5%, 1% and 1% levels, respectively. Whilst large in magnitude and in statistical terms, these coefficients also represent 72.6%, 44.7% and 212% increases in average absolute intraday jumps, further demonstrating their economic importance in driving jumps and confirming the preliminary findings of section 4.5.1.

Despite showing more jumps than the S&P 500 E-Mini futures market, the FTSE 100 futures market exhibits fewer instances of news causing jumps and much lower proportions of jumps relating to US macroeconomic news, as illustrated in Table 4.5.2.5. As the first market that trades outside the US chronologically, this is to be expected since this UK market is closed when some US announcements are made later in the US trading day (most notably FOMC). However, with many announcements occurring early in the morning in New York, numerous releases are captured during the UK trading hours. This is confirmed by the similarities in the proportions of jumps relating to announcements for the GBP-USD and JPY-USD futures markets. Although the numbers and proportions of news items causing jumps are lower for this market, estimated values of β_δ are high (0.157, 0.164 and 0.126) showing statistical significance at the 1% level and large contributions to average absolute intraday jumps. These contributions are large in economic terms since they add on average 37.4% (α=0.001) of the non-announcement average absolute intraday jump, and this is high relative to the EUR-USD and JPY-USD futures markets, but slightly smaller than for the GBP-USD and S&P 500 E-Mini contracts. The notable individual announcements are Consumer Confidence, Initial Claims and the Employment Report showing both large $N(D_{\delta,k}, \kappa_k)$ and statistically significant estimates of β_δ, measuring 0.141, 0.124 and 0.203 respectively for α=0.001. Economically, these increases in average absolute intraday jumps are 30.7%, 27.0% and 44.6% of the non-announcement average jumps. Bank of England and European Central Bank interest rate decisions are the only non-US news included in this sample and both contribute heavily to the size of average absolute intraday jumps for FTSE 100 futures, although only four intraday jumps are caused by these announcements. The large and statistically significant coefficient estimates of 0.253 and 0.118 correspond to increases of 54.9% and 25.5% of the non-announcement average absolute jumps suggesting that, on these rare occasions, these announcements are highly important.

To complete the discussion of the equity index futures, Table 4.5.2.6 illustrates the results for the DJ Euro Stoxx 50 futures market. Confirming the previous results, the proportions of jumps corresponding to US macroeconomic news announcements increases as α falls and the jump test becomes more stringent. These proportions are high for the DJ Euro Stoxx 50 futures, with almost a quarter of all jumps corresponding to news releases for α=0.001, and are similar to those of the EUR-USD and S&P 500 E-Mini futures markets. The impact of news announcements on average absolute jumps is also large in this market and the highest of all markets considered thus far. An estimated β_δ value of 0.247 adds 47.5% to the non-announcement average absolute jumps, which is significant in both statistical and economic terms. Consumer Confidence, GDP Advance and the Employment Report again provide the statistically significant individual announcements, whilst Initial Claims, ISM Index and Retail Sales produce large $N(D_{\delta,k}, \kappa_k)$ values, but no statistically significant effects. Significant β_δ estimates of 0.187, 0.256 and 0.271

measure large increases in the average size of absolute intraday jumps corresponding to additional contributions of 32.6%, 44.6% and 48.0% of their respective averages. Existing Home Sales, GDP Preliminary and ECB announcements also deserve special mention for this market since they also provide large, significant estimates of β_δ for α=0.001, but such large effects rely on only a few instances of news and jumps coinciding.

The role of macroeconomic news in influencing intraday price jumps is more apparent in the interest rate futures markets depicted in Tables 4.5.2.7 to 4.5.2.9 with far more occurrences of jumps corresponding to news announcements. This is particularly evident in Table 4.5.2.7 for US 10-Year Treasury Bond futures. For all news combined, 37.2%, 45.4% and 53.7% of intraday jumps identified correspond to US macroeconomic news announcements across the three statistical significance levels, which are dramatic and the highest of all markets in this sample. Despite these large proportions, the estimated value of β_δ for α=0.001 does not seem extremely high at 0.085, but this is statistically significantly greater than zero at the 1% level and corresponds to an economically significant impact relative to non-announcement average absolute jumps (45.6% of the average). Many individual indicators provide large values of N($D_{\delta,k}$, κ_k) but low statistical significance levels for estimates of β_δ including Business Inventories, Chicago PMI, Construction Spending, Consumer Confidence, Housing Starts, Initial Claims, ISM Index, New Home Sales, New York Empire State Index, PPI and Retail Sales. In support of the findings above, the dominant announcements in terms of numbers of occurrences with jumps and statistical significance are GDP Advance, Employment Report and FOMC. Respectively, 43.8%, 53.8% and 36.4% of these announcements generate intraday jumps in this sample for α=0.001, and corresponding estimates of β_δ of 0.086, 0.262 and 0.087 represent increases in the average absolute intraday jumps of 38.6%, 127% and 39.3% when these important news announcements occur. The Employment Cost Index also deserves mention for this market given its statistically significant coefficient estimate of 0.167 relating to an average 75.2% increment in average absolute intraday jumps but, although important, this is vastly dominated by the tremendous influence of the Employment Report.

Table 4.5.2.8 shows the regression results for the UK Gilt futures. Large numbers of intraday jumps are detected for this market, but, as with the FTSE 100 futures, the proportions of these that are related to US macroeconomic news is quite low (12.8%, 15.9% and 19.4% across significance levels). Estimates of β_δ for all news combined are also low in magnitude, and, although they are statistically significantly greater than zero at the 1% level, they reveal a lower economic significance of news than for the other markets. This is shown by the estimated β_δ of 0.043 for α=0.001, representing an increase in average absolute intraday jumps of 28.1% when jumps correspond with news announcements. Although this seems low compared to other markets, news announcements effects remain a sizeable and important influence on intraday jumps. Individual announcements giving large $N(D_{\delta,k}, \kappa_k)$ but low significance of coefficients include CPI, ISM Index, PPI, Retail Sales and Bank of England interest rate decisions, whilst the important indicators that generate significant effects are the Employment Cost Index, GDP Advance, Initial Claims and the Employment Report. Somewhat surprisingly, the Employment Report shows a stronger influence on Gilt futures than the Bank of England's Monetary Policy Committee, the former adding on average 0.123 to average absolute intraday jumps and measuring an economically significant increment of 78.4% of this average.

Finally, Table 4.5.2.9 completes this analysis by considering the results of the Euro Bund futures. For all news combined, the proportions of jumps associated with news announcements are sizeable, higher than the UK Gilt, but lower than the US 10 Year T-Bond futures. The related estimates of β_δ are also small, but remain statistically significantly greater than zero at the 1% level. In economic terms, the estimate of 0.029 for α=0.001 represents an average addition to absolute jumps of 20.9% of the non-announcement average absolute intraday jumps. As with the previous interest rate futures markets, there are many individual announcements showing large $N(D_{\delta,k}, \kappa_k)$ but low significance of coefficients, and these include Chicago PMI, Construction Spending, Consumer Confidence, CPI, Initial Claims, ISM Index, Michigan Sentiment Preliminary, PPI and Retail Sales for the Euro Bund futures market. The statistically significant releases, that also give numerous $N(D_{\delta,k}, \kappa_k)$, are the Employment Cost Index, GDP Advance and the Employment Report, consistent with other markets. Their coefficient values of 0.062, 0.044 and 0.094 raise the average size of absolute intraday jumps by 42.5%, 30.4% and 66.9% respectively. Bank of England and European Central Bank interest rate announcements are also important in this market, as expected, although they do not provide many occurrences of news and jump coincidence. Their associated coefficient estimates are statistically significantly greater than zero, however, measuring 0.035 and 0.047 corresponding to, on average, 24.1% and 32.4% increments in average absolute intraday jumps.

The results shown so far in this section assume that volatility is constant throughout the trading day. As noted in previous sections, there is a wealth of evidence to suggest that this is an unrealistic assumption and so to circumvent this problem, and to assess the impact of this assumption on these results, the regressions of intraday jumps on news dummy variables are repeated using returns standardised by the intraday volatility patterns measured by average absolute returns.[29] The regression results, similar in presentation to those above, are shown in Tables 4.5.2.10 to 4.5.2.18 for each market and display the following common characteristics. First, as shown in section 4.4, standardising returns by average absolute returns prior to the intraday jump test gives rise to fewer total jumps being detected. Tables 4.5.2.10 to 4.5.2.18 also show that standardisation leads to fewer instances of jumps corresponding to news releases and this is emphasised by the proportions of these coincidences of total intraday jumps falling to approximately half of those for raw returns. In spite of this, estimates of β_δ for 'All News', measuring the impact of news announcements on average intraday jumps, are statistically significantly greater than zero and approximately more than double the corresponding estimates for raw returns for all nine futures markets. This pattern is also present for individual indicators with fewer $N(D_{\delta,k}, \kappa_k)$ being identified, but more announcements showing statistical significance and coefficient estimates suggesting much larger impacts on average intraday jumps for these announcements. The remaining analysis discusses the nuances of each market in turn.

[29] Alternatively, returns may be standardised by the standard deviation per five-minute interval as was performed in section 4.4. Since the results in that analysis are qualitatively similar for both standardisation techniques, only results using standardisation by absolute returns are reported here. As shown in Chapter 3, the separation of news announcement effects from the inherent intraday volatility pattern is both important and challenging. This standardisation procedure is a somewhat crude method for annihilating intraday volatility patterns and there is a danger that true jumps, particularly those relating to US macroeconomc news announcements occurring at the peak of the intraday pattern, may be excluded by this technique. The more sophisticated parametric methods of the previous chapter may improve upon this simple standardisation technique in separating volatility from news, however, such an analysis is left for future work in order to focus here on the main relationships between jumps and news. The consistency of intraday jump detection shown in section 4.5.1 also suggests that intraday jump measurement procedures using raw returns, standardised return and the sequential method are remarkably similar, alleviating potential concerns relating to the accuracy of the simple standardisation procedure implemented here.

Table 4.5.2.10. Intraday Jumps and News Dummy Variables for EUR-USD Futures (Standardised Returns).

α		0.01 No. Jumps: 803		0.001 No. Jumps: 462		0.0001 No. Jumps: 272	
	N($D_{\delta,k}$)	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ
All News	1,840	60	**0.219****	47	**0.220****	34	**0.246****
Business Inventories	84	1	**0.080****	1	**0.052****		
Chicago PMI	82	1	-0.007				
Construction Spending	88	2	**0.160****	1	**0.143****		
Consumer Confidence	89	3	**0.173***	2	**0.229****	2	**0.201****
CPI	88	1	**0.157****				
Current Account	25	1	**0.047****	1	**0.019****		
Employment Cost Index	30	1	**0.296****	1	**0.268****	1	**0.239****
Existing Home Sales	89	1	0.004				
Factory Orders	86	2	0.037	1	**0.080****		
GDP Advance	30	2	**0.410****	2	**0.382****	2	**0.354****
Initial Claims	378	6	**0.119****	4	**0.098***	3	**0.085+**
ISM Manufacturing	88	3	**0.137****	1	**0.143****		
Mich Sentiment Prel	77	2	**0.007+**	2	-0.022	1	-0.050
New Home Sales	88	1	**0.317****	1	**0.289****	1	**0.261****
NY Empire State Index	36	1	**0.080****	1	**0.052****		
Non-Farm Payrolls	81	18	**0.397****	15	**0.401****	12	**0.407****
Personal Income	80	1	**0.058****	1	**0.030****	1	0.001
Personal Spending	80	1	**0.058****	1	**0.030****	1	0.001
PPI	83	3	**0.182****	2	**0.107****	1	**0.133****
Retail Sales	87	2	**0.216****				
Trade Balance	87	5	**0.232****	4	**0.250****	3	**0.263****
Unemployment Rate	81	18	**0.397****	15	**0.401****	12	**0.407****
FOMC	63	16	**0.067***	15	0.044	11	0.050

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in EUR-USD futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, κ_k) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.11. Intraday Jumps and News Dummy Variables for GBP-USD Futures (Standardised Returns).

α		0.01 No. Jumps: 1,031		0.001 No. Jumps: 564		0.0001 No. Jumps: 331	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,950	50	**0.160****	30	**0.195****	25	**0.197****
Chicago PMI	87	1	**0.081****	1	**0.066****	1	**0.046****
Consumer Confidence	95	3	**0.107****	2	**0.096****	1	**0.077****
CPI	94	1	**0.196****	1	**0.181****	1	**0.161****
Factory Orders	91	1	**0.093****	1	**0.077****	1	**0.058****
GDP Advance	32	1	**0.423****	1	**0.408****	1	**0.388****
Initial Claims	400	4	**0.103****	2	**0.049****	1	**0.030****
Mich Sentiment Prel	82	2	-0.014				
New Home Sales	93	1	**0.110****	1	**0.095****		
Non-Farm Payrolls	85	16	**0.293****	9	**0.383****	9	**0.367****
Personal Income	84	1	**0.066****	1	**0.050****	1	**0.030****
Personal Spending	84	1	**0.066****	1	**0.050****	1	**0.030****
PPI	89	2	**0.117****	1	**0.140****		
Retail Sales	93	2	**0.123****				
Trade Balance	92	6	**0.198****	3	**0.247****	1	**0.384****
Unemployment Rate	85	16	**0.293****	9	**0.383****	9	**0.367****
FOMC	66	15	0.024	10	**0.040+**	9	0.024

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in GBP-USD futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.12. Intraday Jumps and News Dummy Variables for JPY-USD Futures (Standardised Returns).

α		0.01 No. Jumps: 820		0.001 No. Jumps: 428		0.0001 No. Jumps: 230	
	N($D_{\delta,k}$)	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ	N($D_{\delta,k}$, κ_k)	β_δ
All News	1,951	39	**0.166****	28	**0.192****	18	**0.216****
Capacity Utilization	88	1	**0.007+**				
Chicago PMI	87	1	**0.772****	1	**0.738****	1	**0.697****
Consumer Confidence	95	2	0.009	1	**0.034****		
Current Account	25	1	**0.029****				
Industrial Production	88	1	**0.007+**				
Initial Claims	401	3	**0.020****				
Mich Sentiment Rev	80	1	-0.076				
New Home Sales	93	2	**0.133****	2	**0.099***		
Non-Farm Payrolls	85	15	**0.275****	13	**0.271****	11	**0.253****
Personal Income	84	1	**0.056****	1	**0.021****		
Personal Spending	84	1	**0.056****	1	**0.021****		
PPI	89	1	**0.172****	1	**0.138****		
Productivity Prel	32	1	**0.225****	1	**0.190****		
Trade Balance	93	5	**0.163***	3	**0.223***	1	**0.464****
Unemployment Rate	85	15	**0.275****	13	**0.271****	11	**0.253****
FOMC	66	10	0.014	8	-0.024	5	-0.046

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in JPY-USD futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, κ_k) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.13. Intraday Jumps and News Dummy Variables for S&P 500 E-Mini Futures (Standardised Returns).

α		0.01 No. Jumps: 591		0.001 No. Jumps: 299		0.0001 No. Jumps: 187	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	2,135	76	**0.398****	52	**0.462****	36	**0.554****
Business Inventories	95	7	**0.157+**	5	0.051	3	0.061
Capacity Utilization	94	3	-0.274	1	-0.426	1	-0.491
Construction Spending	94	1	**0.262****				
Consumer Confidence	96	2	**0.534****	1	**0.373****		
CPI	96	11	0.063	8	-0.032	6	-0.082
Employment Cost Index	32	4	**0.358***	2	**0.488***	1	**0.726****
GDP Advance	32	4	**0.639****	3	**0.716****	2	**0.917****
GDP Prel	32	1	**0.203****	1	**0.110****	1	0.046
Housing Starts	96	2	0.028	1	-0.229	1	-0.293
Industrial Production	94	3	-0.274	1	-0.426	1	-0.491
Initial Claims	413	11	**0.171***	6	0.107	2	0.217
ISM Manufacturing	94	2	**0.401****	1	**0.446****		
Leading Indicators	97	1	**0.262****				
Mich Sentiment Prel	93	1	**0.132****	1	0.038		
NY Empire State Index	36	2	-0.122	1	-0.204	1	-0.269
Non-Farm Payrolls	93	20	**0.432****	17	**0.403****	10	**0.560****
PPI	95	6	**0.181***	3	0.000	1	-0.245
Productivity Prel	31	4	0.006	3	-0.058	2	-0.068
Productivity Rev	32	1	-0.145				
Retail Sales	95	7	**0.115****	4	0.015	3	-0.036
Unemployment Rate	93	20	**0.432****	17	**0.403****	10	**0.560****
FOMC	67	15	**0.802***	10	**1.142****	10	**1.099****

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in S&P 500 E-Mini futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.14. Intraday Jumps and News Dummy Variables for FTSE 100 Futures (Standardised Returns).

α		0.01 No. Jumps: 588		0.001 No. Jumps: 300		0.0001 No. Jumps: 156	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	2,049	44	**0.282****	28	**0.349****	16	**0.367****
Capacity Utilization	94	3	-0.136				
Construction Spending	88	1	**0.448****	1	**0.395****	1	**0.326****
Consumer Confidence	93	2	**0.207****	2	**0.154****		
CPI	95	3	**0.219****	2	**0.260****	1	**0.276****
Employment Cost Index	32	2	**0.591****	2	**0.539****	1	**0.401****
GDP Advance	32	4	**0.407****	4	**0.356****	1	**0.401****
GDP Prel	32	2	**0.141****	1	**0.124****		
Housing Starts	96	1	**0.031****				
Industrial Production	94	3	-0.136				
Initial Claims	406	6	**0.352****	4	**0.328****	2	**0.312****
ISM Manufacturing	87	1	**0.448****	1	**0.395****	1	**0.326****
Mich Sentiment Prel	92	1	**0.793****	1	**0.741****		
Mich Sentiment Rev	93	2	0.179	2	0.126	2	0.056
NY Empire State Index	37	1	-0.139	1	-0.193		
Non-Farm Payrolls	94	13	**0.404****	8	**0.565****	7	**0.556****
Productivity Prel	32	2	**0.191****				
Retail Sales	94	3	**0.274****	1	**0.172****		
Trade Balance	95	1	**0.341****	1	**0.289****	1	**0.219****
Unemployment Rate	94	13	**0.404****	8	**0.565****	7	**0.556****
BOE	95	4	**0.329****	3	**0.308****	2	**0.265****
ECB	115	4	0.043	3	0.033	2	0.016

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in FTSE 100 futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.15. Intraday Jumps and News Dummy Variables for DJ Euro Stoxx 50 Futures (Standardised Returns).

α		0.01 No. Jumps: 575		0.001 No. Jumps: 293		0.0001 No. Jumps: 170	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,969	55	**0.420****	38	**0.420****	26	**0.390****
Business Inventories	89	4	**0.605****	4	**0.520****	3	**0.533****
Capacity Utilization	89	6	-0.099	4	-0.133	3	-0.202
Construction Spending	84	3	**0.352***	1	**0.158****	1	**0.075***
Consumer Confidence	88	2	**0.572****	1	**0.600****	1	**0.518****
CPI	90	4	**0.397****	4	**0.310****	3	**0.252***
Employment Cost Index	30	3	**0.415****	1	**0.207****		
GDP Advance	30	4	**0.348****	2	**0.132***		
GDP Prel	30	1	**0.602****	1	**0.514****	1	**0.432****
Housing Starts	90	1	**0.440****	1	**0.352****	1	**0.269****
Industrial Production	89	6	-0.099	4	-0.133	3	-0.202
Initial Claims	382	7	**0.301****	5	**0.141+**	1	-0.102
ISM Manufacturing	83	3	**0.352***	1	**0.158****	1	**0.075***
Leading Indicators	89	2	**0.156****	1	**0.158****	1	**0.075***
Mich Sentiment Prel	89	3	**0.431***	2	0.038	1	-0.164
Non-Farm Payrolls	89	19	**0.520****	12	**0.672****	7	**0.733****
PPI	88	3	**0.665****	3	**0.579****	2	**0.531***
Productivity Prel	29	2	**0.206***	2	0.118	1	**0.206****
Retail Sales	89	3	**0.315****	2	**0.272+**	1	-0.047
Trade Balance	90	1	**0.070****	1	-0.018	1	-0.102
Unemployment Rate	89	19	**0.520****	12	**0.672****	7	**0.733****
FOMC	3	2	**0.497***	2	**0.409+**	2	0.327
BOE	91	2	-0.076	1	-0.086	1	-0.170
ECB	116	2	**0.686****	2	**0.599****	2	**0.518****

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in DJ Euro Stoxx 50 futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.16. Intraday Jumps and News Dummy Variables for US 10-Year T-Bond Futures (Standardised Returns).

α		0.01 No. Jumps: 630		0.001 No. Jumps: 358		0.0001 No. Jumps: 235	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	1,903	110	**0.186****	77	**0.182****	56	**0.194****
Business Inventories	87	3	**0.234****	1	**0.312****	1	**0.288****
Capacity Utilization	87	8	-0.005	7	-0.062	6	-0.085
Chicago PMI	86	7	0.024	4	0.029	2	0.010
Construction Spending	93	13	**0.060****	6	**0.045+**	4	0.000
Consumer Confidence	95	4	**0.115***	3	**0.100+**	2	**0.154****
CPI	94	8	**0.131****	5	**0.134****	2	**0.158***
Employment Cost Index	32	6	**0.185****	2	**0.284****	1	**0.155****
Factory Orders	90	3	-0.006	1	-0.023		
GDP Advance	32	4	**0.183****	1	**0.387****		
Housing Starts	95	2	**0.070****	1	**0.051****	1	**0.027****
Industrial Production	87	8	-0.005	7	-0.062	6	-0.085
Initial Claims	393	7	**0.172****	2	**0.284****	1	**0.155****
ISM Manufacturing	92	14	**0.084****	7	**0.091***	5	0.069
Leading Indicators	96	2	**0.140****	2	**0.105****	1	**0.073****
Mich Sentiment Prel	77	8	-0.023	6	-0.038	2	-0.032
Mich Sentiment Rev	73	3	**0.072****	3	**0.037+**		
New Home Sales	88	5	**0.053***	4	0.005	3	0.000
NY Empire State Index	36	1	**0.347****	1	**0.312****	1	**0.288****
Non-Farm Payrolls	80	19	**0.496****	15	**0.495****	12	**0.514****
Personal Income	81	1	**0.125****				
Personal Spending	81	1	**0.125****				
PPI	84	1	**0.287****				
Productivity Prel	32	1	**0.159****				
Retail Sales	91	3	**0.219****	2	**0.252****	2	**0.229****
Unemployment Rate	80	19	**0.496****	15	**0.495****	12	**0.514****
FOMC	66	25	**0.119****	23	**0.085****	20	**0.081***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in US 10-Year T-Bond futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.17. Intraday Jumps and News Dummy Variables for UK Gilt Futures (Standardised Returns).

α		0.01		0.001		0.0001	
		No. Jumps: 1,190		No. Jumps: 674		No. Jumps: 421	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	2,034	70	**0.117****	45	**0.136****	39	**0.136****
Business Inventories	92	2	**0.142***	2	**0.122***	2	**0.104***
Capacity Utilization	94	2	-0.046	1	-0.057		
Chicago PMI	90	5	**0.039****				
Consumer Confidence	91	3	**0.113****	2	**0.102****	2	**0.083****
CPI	95	4	**0.130***	2	**0.228****	2	**0.210****
Employment Cost Index	32	5	**0.147****	2	**0.155****	2	**0.137****
GDP Advance	32	6	**0.136****	2	**0.155****	2	**0.137****
Housing Starts	96	2	**0.132+**	1	**0.247****	1	**0.229****
Industrial Production	94	2	-0.046	1	-0.057		
Initial Claims	401	6	**0.139****	3	**0.129****	2	**0.106***
ISM Manufacturing	86	3	**0.073****	1	**0.072****	1	**0.053****
Mich Sentiment Prel	91	6	0.006	3	0.010	2	**0.017+**
New Home Sales	88	1	-0.019				
NY Empire State Index	37	2	**0.142***	2	**0.122***	2	**0.104***
Non-Farm Payrolls	93	22	**0.210****	19	**0.214****	17	**0.216****
PPI	92	2	**0.078****	1	**0.035****	1	**0.016****
Productivity Prel	31	2	**0.142****	1	**0.136****		
Retail Sales	93	2	**0.095****	2	**0.076****	1	**0.097****
Trade Balance	93	1	**0.025****				
Unemployment Rate	93	22	**0.210****	19	**0.214****	17	**0.216****
BOE	94	11	**0.062****	10	**0.050***	10	0.031
ECB	115	2	-0.030	1	-0.052	1	-0.071

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in UK Gilt futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.18. Intraday Jumps and News Dummy Variables for Euro Bund Futures (Standardised Returns).

α		0.01 No. Jumps: 960		0.001 No. Jumps: 539		0.0001 No. Jumps: 339	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ	$N(D_{\delta,k}, \kappa_k)$	β_δ
All News	2,095	87	**0.091****	56	**0.107****	42	**0.108****
Business Inventories	95	3	**0.171****	3	**0.152****	3	**0.134****
Capacity Utilization	95	6	-0.001	4	-0.020	3	-0.045
Chicago PMI	89	3	0.019	2	0.001	1	**0.022****
Construction Spending	90	5	**0.051****	2	**0.065****	1	**0.083****
Consumer Confidence	93	4	**0.064***	1	**0.160****		
CPI	96	2	**0.102+**	2	0.082	1	**0.160****
Employment Cost Index	32	5	**0.111****	3	**0.115****	3	**0.096****
Factory Orders	95	1	-0.008				
GDP Advance	32	5	**0.108****	3	**0.114****	2	**0.118****
Housing Starts	96	1	**0.005***	1	-0.015		
Industrial Production	95	6	-0.001	4	-0.020	3	-0.045
Initial Claims	405	7	**0.114****	4	**0.114****	3	**0.072***
ISM Manufacturing	90	8	**0.072****	4	**0.081****	3	**0.080****
Leading Indicators	95	1	**0.087****				
Mich Sentiment Prel	94	8	0.017	6	0.009	5	0.005
Mich Sentiment Rev	93	1	**0.122****	1	**0.102****	1	**0.083****
NY Empire State Index	37	2	0.004	1	**0.014****	1	-0.005
Non-Farm Payrolls	95	23	**0.199****	17	**0.220****	14	**0.231****
PPI	94	3	**0.173****	3	**0.154****	2	**0.120+**
Productivity Prel	31	1	**0.108****				
Retail Sales	95	3	**0.116****	2	**0.103****	1	**0.141****
Unemployment Rate	95	23	**0.199****	17	**0.220****	14	**0.231****
FOMC	7	4	-0.057	2	-0.062	2	-0.081
BOE	97	4	-0.001	2	**0.036****	1	**0.018****
ECB	118	9	0.018	7	0.014	6	0.011

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in Euro Bund futures returns. Intraday jumps are detected according to equation (4.36) using returns standardised by average absolute returns and across a range of significance levels (α). $N(D_{\delta,k})$ measures the number of each macroeconomic announcement within the sample and $N(D_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.41) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.2.10 displays the results for EUR-USD. On comparison with Table 4.5.2.1, for α=0.001, standardisation of returns reduces the number of jumps by 109 and decreases N($D_{\delta,k}$, κ_k) for all news combined by 119, such that 10.2% of intraday jumps correspond to news announcements, compared to 29.1% for raw returns. Far fewer jumps are caused by news therefore, but those that are show higher average absolute intraday jumps by an incremental 0.220, representing a 94.3% increase, relative to non-announcement average absolute intraday jumps size. Estimated values of β_δ are significantly greater than zero at the 1% level of significance for all news combined and many of the individual announcements, although many of these significant coefficients correspond to only a single announcement. In support of the findings for raw returns, the Employment Report dominates all other indicators in this market. Of the 81 announcements, 15 cause jumps for standardised returns, compared to 38 for raw returns, and these are associated with an increase in average absolute intraday returns of 0.401. This is statistically significant at the 1% level and measures an economically significant incremental rise of 165% of the average absolute intraday jumps not containing these 15 jumps. FOMC interest rate decisions also provide 15 incidences of announcements corresponding to jumps, but these do not generate statistically significant additions to average absolute intraday jumps.

For GBP-USD futures in Tables 4.5.2.2 and 4.5.2.11 there is not such a severe drop in the number of intraday jumps as for EUR-USD after annihilating the intraday volatility pattern (only 28 fewer jumps for α=0.001), but there is a drop of 72 incidences where news and jumps coincide, providing some tentative evidence that standardisation results in the identification of some jumps that were not detected for raw returns. This also suggests that some news announcement jumps are eliminated by the standardisation.[30] Nevertheless, estimates of β_δ for all news combined are more than double those of raw returns, 0.195 representing an increase in average absolute intraday jumps of 116% relative to the average of non-announcement related jumps. As with EUR-USD futures, more individual announcements are statistically significant for standardised returns, but this stong impact on average absolute intraday jumps is often the result of single news announcements. The Employment Report is again the most important indicator, but

[30] Whilst it is desirable to eliminate large returns that are not true jumps, there is a concern that this standardisation technique is slightly rudimentary in separating genuine news-related jumps from the intraday volatility pattern at the times of news releases, which coincide with cyclical peaks in the pattern.

despite only 9 of 85 announcements corresponding to jumps, these announcements raise average absolute intraday jumps by 0.383 or 222%.

To complete the analysis of foreign exchange futures markets, Table 4.5.2.12 shows the results for JPY-USD futures for standardised returns. Confirming the general finding, standardisation leads to fewer jumps being detected, fewer jumps corresponding with news announcements and the proportions of these coincidences to total jumps are approximately half of the same proportions for raw returns. For all news combined, these fewer announcements generate much greater influence on average absolute intraday jumps with β_δ estimated at 0.192, which is approximately three times the size of the coefficient for raw returns and represents an incremental increase in average absolute intraday jumps of 80.1%, which is lower than obtained for both EUR-USD and GBP-USD futures. Occasional single announcements produce statistically significant reactions in absolute intraday jumps (Chicago PMI, Consumer Confidence, Personal Income, Personal Spending, PPI, Productivity Preliminary), but the Employment Report stands out once again as the dominant indicator with 13 of 85 announcements generating an increase in average absolute intraday jumps of 0.192, or 111% of average absolute non-announcement jumps.

Very similar findings emerge for S&P 500 E-Mini futures in Table 4.5.2.13 with a large fall in the proportion of jumps associated with news. The β_δ estimate for all news combined is double that of raw returns at 0.462 and this measures a 107% increase in average absolute intraday jumps. However, the jumps related to announcements that remain in the sample following standardisation of returns provide a dramatic influence on jumps. In contrast to the foreign exchange futures markets, for S&P 500 E-Mini futures some individual indicators, which have $N(D_{\delta,k}, \kappa_k)$ greater than one, (Business Inventories, Employment Cost Index, Initial Claims and Retail Sales) do not show statistically significant effects on average absolute intraday jumps. Other indicators display smaller numbers of $N(D_{\delta,k}, \kappa_k)$ and statistically significant reactions in absolute jumps showing that occasional announcements can have dramatic influences (Consumer Confidence, Employment Cost Index, GDP Advance, GDP Preliminary, ISM Index). The Employment Report and FOMC interest rate decisions are the two dominant indicators in this market, consistent with the results of Table 4.5.2.4 using raw returns, and they coincide with intraday jumps on 17 and 10 occasions, show statistically positive β_δ estimates of

0.403 and 1.142 at the 1% level, relating to increases in average absolute intraday jumps of 82.1% and 240% respectively.

For FTSE 100 futures, US macroeconomic news (and Bank of England and European Central Bank) announcements generate an increase in average absolute intraday jumps of 0.349 (92.5%), as shown in Table 4.5.2.14, which is a much larger reaction than for the raw returns. This measures the average reaction across 28 announcement-related jumps out of a possible 300 jumps (9.3%). When considered in isolation, many more indicators show statistically significant impacts on jumps as compared to raw returns, but with low $N(D_{\delta,k}, \kappa_k)$ figures, and the Employment Report again stands out as the most important indicator adding 0.565 (143%) to average absolute intraday jumps. Other indicators that deserve mention are GDP Advance (88.0%) and Bank of England interest rate decisions (75.9%) whose announcements also cause severe jumps on rare occasions.

The final equity market considered is the DJ Euro Stoxx 50 futures market and these results are displayed in Table 4.5.2.15. Estimates of β_δ are almost double those for raw returns and, specifically for α=0.001, news announcements generate an increase in average absolute intraday jumps of 0.420 (88.0%). There is a noticeable increase in the number of individual announcements showing statistically significant estimates of β_δ for standardised returns, but, as with other markets, most of them are caused by single news items. There are some large reactions in jumps for these rare releases such as Business Inventories (0.520), Consumer Confidence (0.600), GDP Preliminary (0.514), PPI (0.579) and ECB (0.599), but these are all smaller than the effect of the Employment Report (0.672), which raises average absolute intraday jumps by 133% on average over 12 important announcements.

Table 4.5.2.16 shows the results for the US 10-Year T-Bond futures market. The proportion of jumps corresponding to news (21.5%) is the largest of all nine markets, confirming the findings of the previous section that the US 10-Year T-Bond futures market is the most responsive to US macroeconomic news announcements. Despite a dramatic fall in this proportion after standardising, the impact of these remaining news items on jumps rises forcefully. Estimates of β_δ for all news increase from 0.085 for raw returns to 0.182 for standardised returns, both of which are statistically significant at the 1% level, and corresponds to an increase in the addition to average absolute intraday jumps of 97.3% from 45.6% for raw returns. This implies that the absolute value of intraday jumps almost doubles, on average, when

US macroeconomic news is announced, showing the economic significance of these news releases. The important individual indicators in terms of the statistical significance of coefficients are Business Inventories, CPI, Employment Cost Index, GDP Advance, Housing Starts, Initial Claims, ISM Index, Leading Indicators, NY Empire State Index and Retail Sales, although these often show single or few instances of news coinciding with jumps. Of far greater importance is the Employment Report, consistent with previous results, showing that 15 of the total 80 announcements cause intraday jumps and these releases add an average of 0.495 to average absolute intraday jumps, which constitutes a huge rise of 241% (127% for raw returns) relative to average absolute jumps not related to announcements. FOMC interest rate decisions also warrant discussion since a sizeable 23 out of a possible 66 announcements cause jumps. The impact of these on average absolute intraday jumps, although statistically significant at the 1% level, is 0.085, corresponding to an increase of 38.4%, which is very similar to that for raw returns. These figures therefore show that standardisation has very little effect on the jumps caused by FOMC announcements.

In contrast to the large proportion of intraday jumps associated with news for standardised returns for US 10-Year T-Bond futures, the UK Gilt futures market in Table 4.5.2.17 show a much lower proportion at 6.7%, similar to results for GBP-USD and JPY-USD futures. However, the impact of these news announcements on intraday jumps is highlighted by the estimated value of β_δ of 0.136 (more than three times that for raw returns), which corresponds to an average increase of 94.4% in average absolute intraday jumps when US macroeconomic news is announced. Many more individual indicators show statistically significant coefficient estimates after standardisation, albeit with low figures for N($D_{\delta,k}$, κ_k). The Employment Report again shows the greatest influence on intraday jumps with 19 of 93 announcements causing jumps and, although 0.214 is not the largest estimate of β_δ in the table, this represents an economically significant average increase of 145% of average absolute intraday jumps. Bank of England interest rate announcements also display an important role with 10 of 94 announcments causing jumps and 0.050 (32.7%) added to average absolute intraday jumps. Similar to the US interest rate futures market therefore, the influence of domestic interest rate decisions is unaffected by the standardisation of returns.

Finally, the Euro Bund futures market results displayed in Table 4.5.2.18 show that the influence of news announcements is trebled after standardisation, suggesting that standardisation retains the news items causing largest returns. The statistically significant impact of all news combined is measured by an increase in average absolute intraday Euro Bund futures returns of 0.107. Economically, this represents an 80.1% increase over the non-announcement intraday jumps. The statistical significance of coefficient estimates for individual indicators increases for standardised returns and although many of these are again related to isolated announcements, some N($D_{\delta,k}$, κ_k) lie between one and five. Of 118 ECB interest rate announcements, 7 cause jumps, the second highest value of N($D_{\delta,k}$, κ_k) in the table, but these do not provide a statistically significant influence. Consistent with other markets, the Employment Report is dominant with 17 of 95 possible announcements causing jumps and adding, on average, 0.220 to average absolute intraday jumps, which constitutes an increase of 160%.

To conclude this section, regressions of absolute intraday jumps on US macroeconomic news announcement dummies have revealed that intraday jumps are heavily influenced by data releases. For all news combined, there is a statistically and economically significant increase in the value of average absolute intraday jumps when news is released for all nine futures markets and for EUR-USD, S&P 500 E-Mini and US 10-Year T-Bond futures in particular. Some individual indicators are also extremely important, and have been identified separately for each market above, but the Employment Report dominates all others, showing frequent and dramatic influences across all markets, including those traded in Europe and the UK, followed by FOMC interest rate announcements and GDP Advance figures. These interesting and important findings are robust to the extraction of the inherent intraday volatility pattern in high frequency returns. Moreover, although standardisation of returns generates fewer instances of news causing jumps, the removal of smaller intraday jumps magnifies the influence of macroeconomic news on intraday jumps considerably.

4.5.3 Sequential Intraday Jumps and News Dummy Variables

The previous section considered the influence of news on intraday jumps. This section performs an identical analysis using the alternative sequential intraday jump detection technique described in sections 4.3.5 and 4.4.6 in order to assess the relative importance of jump measurement within this context. More specifically, an important change of notation differentiates the use of sequential intraday jumps ($\widetilde{\kappa}_k$) in the regression equation,

$$|\widetilde{\kappa}_k| = \omega_\delta + \beta_\delta D_{\delta,k} + \varepsilon_{\delta,k}\,. \tag{4.42}$$

This section also investigates the use of $Z_{I,t}$ and $U_{I,t}$ defined in equations (4.28) and (4.29) using the staggered versions of realised bipower variation and tripower quarticity of equations (4.33) and (4.34) as two alternative test statistics for detecting intraday jumps. Tables 4.5.3.1 to 4.5.3.9 show the important regression results for sequential intraday jumps detected using $Z_{I,t}$ including the total number of intraday jumps in each regression, the total number of announcements for each news category (N($D_{\delta,k}$)) and the number of coincidences of intraday jumps and news announcements (N($D_{\delta,k}$, $\widetilde{\kappa}_k$)). Consistent with the previous section, the tables also show the results of a single regression combining all news dummies into a single variable (All News).

The general finding emerging from these tables is that both the proportion of jumps related to news announcements and the estimated coefficients measuring the impact of these announcements on intraday jumps tend to lie between the corresponding results for raw returns and standardised returns intraday jumps in the previous section. Proportions in many cases are lower than for raw return intraday jumps, but β_δ are higher. The following review details the interesting features of each market in turn.

Table 4.5.3.1 displays the results for EUR-USD futures. Concentrating on a significance level α=0.001 for the jump test, as suggested by the existing literature, the sequential intraday jump method using the $Z_{I,t}$ test statistic finds fewer intraday jumps (239) than the previous section for both raw (571) and standardised returns (462). Combining all news into one variable, 76 of these sequential intraday jumps correspond to news announcements, a proportion of 31.8%, which is higher than both jump measures of section 3.5.2. Although most markets show proportions of jumps caused by news lying between the corresponding proportions for raw and standardised returns, EUR-USD futures is a notable exception.

Table 4.5.3.1. Sequential Intraday Jumps ($Z_{1,t}$) and News Dummy Variables for EUR-USD Futures.

A		0.01 No. Jumps: 476		0.001 No. Jumps: 239		0.0001 No. Jumps: 126	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	1,840	111	**0.139****	76	**0.156****	52	**0.204****
Business Inventories	84	5	0.045	4	-0.009	1	-0.003
Chicago PMI	82	5	-0.018	2	-0.058	2	-0.098
Construction Spending	88	5	0.038	3	-0.010	2	-0.069
Consumer Confidence	89	11	0.044	7	0.033	4	0.043
CPI	88	5	**0.064***	3	0.052	2	-0.015
Current Account	25	1	**0.046****	1	0.004	1	-0.036
Employment Cost Index	30	2	**0.164***	1	**0.253****	1	**0.214****
Existing Home Sales	89	4	0.010	4	-0.033	1	-0.079
Factory Orders	86	4	0.000	3	-0.045	2	-0.047
GDP Advance	30	5	**0.177***	3	**0.263****	2	**0.331****
GDP Prel	27	1	**0.046****	1	0.004		
Housing Starts	89	2	-0.058				
Initial Claims	378	16	**0.046***	13	0.011	9	-0.003
ISM Manufacturing	88	6	**0.047+**	3	-0.010	2	-0.069
Leading Indicators	90	2	-0.079	1	-0.168		
Mich Sentiment Prel	77	2	-0.060	1	-0.168	1	-0.209
New Home Sales	88	4	**0.116***	3	**0.131***	1	**0.236****
NY Empire State Index	36	5	**0.053***	4	**0.036+**	1	-0.003
Non-Farm Payrolls	81	27	**0.295****	22	**0.293****	17	**0.336****
Personal Income	80	3	-0.038	2	-0.076	2	-0.117
Personal Spending	80	3	-0.038	2	-0.076	2	-0.117
PPI	83	6	**0.082***	5	**0.071+**	3	**0.101***
Productivity Prel	30	1	**0.096****	1	**0.054****	1	0.014
Productivity Rev	30	1	0.006				
Retail Sales	87	7	0.030	3	**0.095+**	3	0.055
Trade Balance	87	10	**0.123****	6	**0.157***	6	**0.119+**
Unemployment Rate	81	27	**0.295****	22	**0.293****	17	**0.336****
FOMC	63	8	**0.105***	6	**0.095+**	4	0.067

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in EUR-USD futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.2. Sequential Intraday Jumps ($Z_{1,t}$) and News Dummy Variables for GBP-USD Futures.

α		0.01 No. Jumps: 861		0.001 No. Jumps: 481		0.0001 No. Jumps: 286	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	1,950	92	**0.102****	54	**0.142****	39	**0.166****
Business Inventories	90	3	0.084	2	**0.125****	1	**0.158****
Chicago PMI	87	3	**0.047***	2	**0.063****	2	**0.050****
Construction Spending	94	6	0.010	3	-0.008	1	-0.059
Consumer Confidence	95	6	**0.048***	5	**0.056***	3	**0.050+**
CPI	94	4	**0.124****	4	**0.115****	3	**0.114****
Current Account	25	2	**0.021***	1	**0.024****	1	**0.012***
Existing Home Sales	94	2	-0.013	2	-0.023	1	-0.038
Factory Orders	91	2	**0.051+**	1	**0.094****	1	**0.081****
GDP Advance	32	4	**0.167***	2	**0.207+**	1	-0.024
GDP Final	31	1	-0.067				
Initial Claims	400	13	**0.033***	7	**0.054***	5	**0.056***
ISM Manufacturing	94	6	0.010	3	-0.008	1	-0.059
Leading Indicators	97	1	-0.069	1	-0.078	1	-0.091
Mich Sentiment Prel	82	3	-0.005	1	-0.019		
New Home Sales	93	2	0.048	2	0.038		
NY Empire State Index	36	3	**0.096****	1	**0.171****	1	**0.158****
Non-Farm Payrolls	85	25	**0.209****	14	**0.295****	12	**0.324****
Personal Income	84	2	0.005	1	**0.067****	1	**0.054****
Personal Spending	84	2	0.005	1	**0.067****	1	**0.054****
PPI	89	8	0.008	3	**0.063+**	2	**0.105****
Productivity Prel	32	1	**0.008****	1	-0.002		
Retail Sales	93	11	-0.004	3	-0.036	1	-0.036
Trade Balance	92	9	**0.132****	6	**0.192****	5	**0.189****
Unemployment Rate	85	25	**0.209****	14	**0.295****	12	**0.324****
FOMC	66	5	**0.070***	3	**0.110****	3	**0.098****

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in GBP-USD futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.3. Sequential Intraday Jumps ($Z_{1,t}$) and News Dummy Variables for JPY-USD Futures.

α		0.01 No. Jumps: 513		0.001 No. Jumps: 253		0.0001 No. Jumps: 121	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	1,951	50	**0.123****	28	**0.168****	20	**0.174****
Business Inventories	90	2	**0.057***	2	0.023		
Chicago PMI	87	3	0.180	2	0.313	2	0.265
Construction Spending	94	2	-0.028				
Consumer Confidence	95	4	**0.025+**	1	-0.042		
CPI	94	1	**0.093****	1	**0.059****		
Employment Cost Index	32	1	-0.039				
Existing Home Sales	94	1	-0.008	1	-0.042		
Factory Orders	91	1	**0.035****				
GDP Advance	32	1	-0.039				
Initial Claims	401	7	-0.033	2	-0.064		
ISM Manufacturing	94	1	-0.011				
Mich Sentiment Rev	80	1	-0.069				
New Home Sales	93	2	**0.141****				
Non-Farm Payrolls	85	15	**0.270****	12	**0.279****	11	**0.235****
PPI	89	3	0.048	2	0.067	1	**0.097****
Retail Sales	93	2	-0.044	2	-0.078	2	-0.130
Trade Balance	93	9	**0.093+**	5	0.114	3	**0.170+**
Unemployment Rate	85	15	**0.270****	12	**0.279****	11	**0.235****
FOMC	66	5	0.017	3	-0.014	2	-0.107

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in JPY-USD futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.4. Sequential Intraday Jumps ($Z_{l,t}$) and News Dummy Variables for S&P 500 E-Mini Futures.

α		0.01 No. Jumps: 318		0.001 No. Jumps: 129		0.0001 No. Jumps: 57	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	2,135	70	**0.368****	45	**0.393****	30	**0.267+**
Business Inventories	95	6	0.017	5	-0.128	3	-0.497
Chicago PMI	96	3	0.052	1	-0.334	1	-0.613
Construction Spending	94	3	0.044	1	0.061	1	-0.214
Consumer Confidence	96	5	**0.211+**	4	0.173	3	-0.129
CPI	96	12	-0.015	9	-0.165	6	-0.502
Employment Cost Index	32	1	**0.838****	1	**0.684****		
Existing Home Sales	96	1	-0.267	1	-0.427	1	-0.707
Factory Orders	95	3	-0.054	2	-0.369	1	-0.613
GDP Advance	32	2	**1.027****	2	**0.877****	1	**0.792****
GDP Prel	32	1	**0.160****				
Housing Starts	96	3	-0.059	3	-0.221	2	-0.460
Initial Claims	413	5	0.147	3	0.141	1	-0.617
ISM Manufacturing	94	4	0.158	1	0.061	1	-0.214
Leading Indicators	97	1	**0.218****	1	0.061	1	-0.214
New Home Sales	95	1	-0.060	1	-0.218	1	-0.496
NY Empire State Index	36	2	-0.166	2	-0.327	1	-0.592
Non-Farm Payrolls	93	21	**0.341****	15	**0.250***	9	0.176
Personal Income	93	1	-0.292				
Personal Spending	93	1	-0.292				
PPI	95	4	-0.014	2	-0.110	1	-0.568
Productivity Prel	31	2	-0.034				
Retail Sales	95	4	**0.065***	3	-0.081	1	-0.304
Trade Balance	96	2	-0.121				
Unemployment Rate	93	21	**0.341****	15	**0.250***	9	0.176
FOMC	67	7	**1.495****	5	**1.885****	5	**1.690****

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in S&P 500 E-Mini futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{l,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.5. Sequential Intraday Jumps ($Z_{l,t}$) and News Dummy Variables for FTSE 100 Futures.

α		0.01 No. Jumps: 426		0.001 No. Jumps: 193		0.0001 No. Jumps: 97	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	2,049	37	**0.212****	17	**0.255****	10	**0.211***
Business Inventories	92	1	-0.201	1	-0.273	1	-0.341
Construction Spending	88	1	-0.013	1	-0.084	1	-0.152
Consumer Confidence	93	2	**0.111****	1	**0.081****		
CPI	95	3	0.133	2	0.021	1	-0.341
Employment Cost Index	32	3	**0.364***	2	0.151	2	0.085
GDP Advance	32	6	**0.247***	4	0.146	2	0.085
GDP Prel	32	3	**0.156****	2	**0.057***		
Initial Claims	406	7	**0.245****	5	0.099	3	0.123
ISM Manufacturing	87	1	-0.013	1	-0.084	1	-0.152
Mich Sentiment Prel	92	1	-0.220				
Mich Sentiment Rev	93	2	-0.142				
NY Empire State Index	37	1	-0.201	1	-0.273	1	-0.341
Non-Farm Payrolls	94	13	**0.343****	5	**0.609****	4	**0.542****
PPI	93	1	-0.151				
Productivity Prel	32	2	**0.178****	1	0.015	1	-0.052
Retail Sales	94	1	**0.213****				
Trade Balance	95	1	**0.329****	1	**0.258****	1	**0.193****
Unemployment Rate	94	13	**0.343****	5	**0.609****	4	**0.542****
BOE	95	2	0.139				

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in FTSE 100 futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{l,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.6. Sequential Intraday Jumps ($Z_{1,t}$) and News Dummy Variables for DJ Euro Stoxx 50 Futures.

α		0.01 No. Jumps: 618		0.001 No. Jumps: 310		0.0001 No. Jumps: 157	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	1,969	85	0.276**	59	0.306**	39	0.362**
Business Inventories	89	6	0.408*	5	0.477**	4	0.543**
Capacity Utilization	89	1	-0.173	1	-0.217		
Chicago PMI	86	4	-0.036	2	-0.207		
Construction Spending	84	7	0.202+	3	0.281+	2	0.426**
Consumer Confidence	88	7	0.087	5	0.103	2	0.119
CPI	90	7	0.192+	5	0.272*	5	0.197+
Employment Cost Index	30	3	0.172+	2	0.042	2	-0.035
Factory Orders	89	3	0.235	2	0.319	1	0.725**
GDP Advance	30	6	0.141*	5	0.057	3	-0.123
GDP Final	30	1	-0.218				
GDP Prel	30	4	0.052	3	0.053	3	-0.025
Housing Starts	90	3	0.064	2	0.094	2	0.018
Industrial Production	89	1	-0.173	1	-0.217		
Initial Claims	382	11	0.132*	8	0.078	6	0.012
ISM Manufacturing	83	9	0.222*	5	0.269*	2	0.426**
Leading Indicators	89	2	0.204**	1	0.251**	1	0.175**
Mich Sentiment Prel	89	1	0.057**	1	0.013		
Mich Sentiment Rev	89	2	-0.066	1	-0.218		
New Home Sales	90	3	-0.058				
NY Empire State Index	37	3	-0.121	1	-0.073		
Non-Farm Payrolls	89	21	0.463**	16	0.457**	13	0.457**
Personal Income	88	1	0.163**				
Personal Spending	88	1	0.163**				
PPI	88	7	0.304*	5	0.456**	3	0.601**
Productivity Prel	29	4	0.200**	3	0.155+	2	0.135
Productivity Rev	30	3	0.037	1	-0.198		
Retail Sales	89	8	0.084	6	0.126	4	0.043
Trade Balance	90	1	0.118**	1	0.075**	1	-0.002
Unemployment Rate	89	21	0.463**	16	0.457**	13	0.457**
FOMC	3	1	0.899**				
ECB	116	2	0.734**	2	0.692**	2	0.619**

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in DJ Euro Stoxx 50 futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.7. Sequential Intraday Jumps ($Z_{I,t}$) and News Dummy Variables for US 10-Year T-Bond Futures.

α		0.01 No. Jumps: 879		0.001 No. Jumps: 517		0.0001 No. Jumps: 312	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	1,903	208	**0.167****	142	**0.184****	94	**0.204****
Business Inventories	87	13	**0.119****	8	**0.088+**	5	**0.130+**
Capacity Utilization	87	6	0.011	1	-0.038	1	-0.057
Chicago PMI	86	8	**0.055***	7	0.037	5	-0.002
Construction Spending	93	22	**0.058****	14	**0.035+**	6	0.022
Consumer Confidence	95	12	0.035	7	0.023	4	-0.004
CPI	94	22	**0.129****	13	**0.117****	12	**0.107****
Current Account	25	2	**0.101****	2	**0.079***	1	-0.002
Employment Cost Index	32	8	**0.251****	8	**0.230****	6	**0.265****
Existing Home Sales	94	5	0.023	1	-0.099	1	-0.118
Factory Orders	90	8	**0.020+**	5	0.006	3	-0.029
GDP Advance	32	10	**0.186****	8	**0.203****	5	**0.255****
GDP Final	31	2	-0.007				
GDP Prel	29	4	0.007	3	0.005	1	-0.042
Housing Starts	95	9	**0.063****	6	0.034	5	0.029
Industrial Production	87	6	0.011	1	-0.038	1	-0.057
Initial Claims	393	35	**0.085****	26	**0.092****	17	**0.105****
ISM Manufacturing	92	23	**0.080****	15	**0.068***	6	**0.039+**
Leading Indicators	96	4	**0.092***	4	**0.070+**	3	0.016
Mich Sentiment Prel	77	3	-0.011	1	**0.045****		
Mich Sentiment Rev	73	2	**0.149****	2	**0.127****	1	**0.103****
New Home Sales	88	8	**0.062***	7	0.035	5	0.025
NY Empire State Index	36	7	**0.110***	5	**0.099+**	4	**0.122***
Non-Farm Payrolls	80	32	**0.382****	29	**0.394****	21	**0.415****
Personal Income	81	3	**0.115****	3	**0.093****	1	**0.134****
Personal Spending	81	3	**0.115****	3	**0.093****	1	**0.134****
PPI	84	13	**0.076****	9	0.042	4	**0.095+**
Productivity Prel	32	4	**0.094***	3	0.051	2	**0.092***
Retail Sales	91	27	**0.093****	18	**0.090****	13	**0.083****
Trade Balance	90	3	0.055	2	-0.038	1	-0.044
Treasury Budget	86	1	-0.113	1	-0.135		
Unemployment Rate	80	32	**0.382****	29	**0.394****	21	**0.415****
FOMC	66	17	**0.191****	9	**0.160***	9	**0.143***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in US 10-Year T-Bond futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{I,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.8. Sequential Intraday Jumps ($Z_{1,t}$) and News Dummy Variables for UK Gilt Futures.

α		0.01 No. Jumps: 997		0.001 No. Jumps: 560		0.0001 No. Jumps: 320	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	2,034	109	**0.072****	78	**0.080****	50	**0.095****
Business Inventories	92	3	**0.110***	2	**0.130***	2	**0.108***
Capacity Utilization	94	4	-0.055	1	-0.057		
Chicago PMI	90	6	0.002	3	-0.004	2	-0.040
Construction Spending	87	7	**0.049+**	2	**0.035+**	1	-0.018
Consumer Confidence	91	8	0.011	6	0.014	3	-0.035
CPI	95	8	0.065	6	**0.069+**	3	**0.120+**
Employment Cost Index	32	7	**0.100****	5	**0.061+**	3	**0.110****
Factory Orders	96	5	-0.018	2	0.022	2	-0.001
GDP Advance	32	8	**0.104****	6	**0.070***	4	**0.078***
GDP Final	31	1	-0.010	1	-0.027		
Housing Starts	96	2	**0.136+**	2	0.120	1	**0.233****
Industrial Production	94	4	-0.055	1	-0.057		
Initial Claims	401	11	**0.066***	8	0.041	4	**0.098****
ISM Manufacturing	86	10	**0.058****	4	**0.052****	2	0.008
Leading Indicators	94	2	**0.041+**	1	**0.065****		
Mich Sentiment Prel	91	5	0.007	4	-0.008	2	-0.025
Mich Sentiment Rev	92	1	**0.021****	1	0.004	1	-0.018
New Home Sales	88	3	-0.044	1	-0.031		
NY Empire State Index	37	2	**0.146****	2	**0.130****	2	**0.108***
Non-Farm Payrolls	93	25	**0.188****	25	**0.175****	21	**0.186****
Personal Income	87	1	-0.016				
Personal Spending	87	1	-0.016				
PPI	92	7	0.022	6	0.002	5	-0.038
Productivity Prel	31	2	**0.146****	2	**0.130****	2	**0.108****
Productivity Rev	32	1	**0.083****	1	**0.066****	1	**0.044****
Retail Sales	93	10	0.024	7	-0.024	5	-0.054
Trade Balance	93	1	**0.029****	1	**0.013****		
Unemployment Rate	93	25	**0.188****	25	**0.175****	21	**0.186****
BOE	94	6	**0.043****	4	**0.040****	2	**0.011+**

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in UK Gilt futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.9. Sequential Intraday Jumps ($Z_{1,t}$) and News Dummy Variables for Euro Bund Futures.

α		0.01 No. Jumps: 740		0.001 No. Jumps: 393		0.0001 No. Jumps: 232	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	2,095	153	**0.066****	100	**0.076****	70	**0.090****
Business Inventories	95	6	**0.102***	4	**0.109***	4	**0.087+**
Capacity Utilization	95	6	-0.020	2	-0.060	1	-0.089
Chicago PMI	89	7	0.013	5	-0.015	4	-0.029
Construction Spending	90	10	**0.026+**	6	0.021	2	**0.050***
Consumer Confidence	93	12	0.005	6	-0.026		
CPI	96	11	0.024	5	0.031	4	0.017
Current Account	25	1	**0.010****				
Employment Cost Index	32	9	**0.093****	9	**0.073****	7	**0.054***
Existing Home Sales	93	3	-0.022	2	-0.025		
Factory Orders	95	5	-0.008	3	-0.035		
GDP Advance	32	11	**0.090****	10	**0.068****	8	**0.048***
GDP Final	32	3	-0.019	1	-0.040		
GDP Prel	32	1	-0.021				
Housing Starts	96	5	0.008	2	-0.015	1	-0.047
Industrial Production	95	6	-0.020	2	-0.060	1	-0.089
Initial Claims	405	28	**0.029***	17	**0.040***	12	**0.036+**
ISM Manufacturing	90	13	**0.047****	9	**0.047***	5	**0.065****
Leading Indicators	95	1	**0.096****	1	**0.076****		
Mich Sentiment Prel	94	9	0.008	6	-0.009	5	-0.026
Mich Sentiment Rev	93	2	0.036	1	**0.111****	1	**0.088****
New Home Sales	93	6	-0.016	3	-0.034	1	-0.074
NY Empire State Index	37	5	0.003	3	-0.016	3	-0.040
Non-Farm Payrolls	95	28	**0.169****	24	**0.171****	22	**0.171****
Personal Income	93	3	-0.013	1	-0.021	1	-0.045
Personal Spending	93	3	-0.013	1	-0.021	1	-0.045
PPI	94	10	**0.087****	7	**0.084***	6	**0.067+**
Productivity Prel	31	3	0.045	2	**0.083****	2	**0.060****
Retail Sales	95	16	**0.037****	10	**0.028+**	6	0.027
Trade Balance	96	3	0.013	1	**0.037****	1	**0.013***
Unemployment Rate	95	28	**0.169****	24	**0.171****	22	**0.171****
BOE	97	1	**0.066****	1	**0.045****	1	**0.022****
ECB	118	4	**0.087****	3	**0.083****	2	**0.036***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in Euro Bund futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $Z_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

In addition to this high proportion, which is similar to that for raw returns, news announcements increase average absolute sequential intraday jumps by 0.156, which is statistically significant at the 1% level and corresponds to an increase of 71.0% relative to average absolute jumps for non-announcement jumps, an effect that is far greater than for raw returns (0.069, 27.4%) in the previous section, but smaller than for standardised returns (0.220, 94.3%). For individual indicators, values of N($D_{\delta,k}$, $\widetilde{\kappa}_k$) are noticeably higher than standardised returns, but fewer of them show statistically significant effects. Announcements of particular interest in terms of N($D_{\delta,k}$, $\widetilde{\kappa}_k$) are Consumer Confidence, Initial Claims, PPI, Retail Sales and FOMC, but estimated values of β_δ are statistically significant at the 10% level at best. GDP Advance provides a large reaction in absolute jumps, significant at the 1% level, but only 3 of a possible 30 announcements cause sequential intraday jumps. Consistent with section 4.5.2, the Employment Report causes the most dramatic effect with 22 of 81 announcements causing intraday jumps and adding an average 0.293% to average absolute sequential intraday jumps, some 120% in relative terms.

The results for GBP-USD futures are presented in Table 4.5.3.2 and show that 11.2% of sequential intraday jumps correspond to news announcements. During these five-minute intervals containing news announcements, absolute intraday jumps are larger on average by 0.142 than for the identified jumps not coinciding with news. This represents an increase in the size of jumps in absolute terms of 97.1%, on average, during announcement intervals, which is significant at the 1% level. Similar results are obtained for individual indicators where Consumer Confidence, CPI, Initial Claims and Trade Balance have higher figures of N($D_{\delta,k}$, $\widetilde{\kappa}_k$) compared to standardised returns, yet retain their statistical significance, which is in contrast to the results for raw returns. The Employment Report remains dominant for GBP-USD futures, increasing average absolute sequential intraday jump by 0.295 (192%) on average over the 14 intervals during which announcements cause jumps. FOMC interest rate decisions deserve special mention for this market since N($D_{\delta,k}$, $\widetilde{\kappa}_k$) has decreased to only 3 for sequential intraday jumps ($Z_{1,t}$), but this has caused the effect on absolute intraday jumps to become statistically significant at the 1% level compared to both methods of the previous section.

For JPY-USD futures, the sequential method finds exactly the same number of intraday jumps (α=0.001) coinciding with news announcements as the method using standardised returns in the previous section, as shown in Table 4.5.3.3. This occurs for a lower total number of intraday jumps, but other data in the table relating to the individual announcements reveal that these intraday jumps are different between the two methods. This is exemplified by the measure of β_δ of 0.168, which is lower for sequential intraday jumps than standardised returns intraday jumps, but this is no less important in statistical or economic terms since these news items increase average absolute sequential intraday jumps by 74.5%. The sequential method shows fewer individual indicators causing intraday jumps in JPY-USD futures than section 4.5.2, but confirms that the Employment Report remains as the only important release with 12 announcements increasing absolute sequential intraday jumps by 0.279 (121%) on average.

Turning to the equity index futures markets, Table 4.5.3.4 illustrates the regression results for S&P 500 E-Mini futures. Along with the EUR-USD futures market, the S&P 500 E-Mini is the only other contract to show a larger proportion of sequential intraday jumps coinciding with all news (34.9%) than for raw returns intraday jumps. The estimate of β_δ remains significantly positive for all news combined, showing an enormous average increase in absolute intraday jumps of 0.393 (81.2%) when these news announcements occur. The interesting individual announcements are GDP Advance, Employment Report and FOMC. The two announcements of GDP Advance causing sequential intraday jumps increase their average absolute value by 0.877 (144%), whilst the 15 Employment Report data releases raise this average by 0.250 (42.2%), but this is significant at only the 5% level. FOMC decisions are interesting since the sequential method identifies 5 fewer instances of these releases causing intraday jumps, but the remaining 5 announcements increase the reaction in absolute jump values compared to the previous section. The estimated β_δ of 1.885 corresponds to a huge increase in average absolute sequential intraday jumps of 344% relative to non-announcement jumps.

FTSE 100 futures results are shown in Table 4.5.3.5 and the N($D_{\delta,k}$, $\widetilde{\kappa}_k$) figure for all news combined illustrates a lower proportion of total jumps caused by news announcements (8.80%) than both methods of the previous section. Despite this, news announcements related to jumps generate an average increase in absolute sequential intraday jumps of 0.255 (61.2%), which is statistically significant at the 1% level and lies between the corresponding figures for raw and standardised returns intraday jumps. The relatively few jumps caused by news, therefore, are found to have a pronounced influence on the absolute size of jumps. This is also the case for the Employment Report, the only individual indicator to exhibit a systematic impact on sequential intraday jumps, with only 5 announcements causing jumps but contributing an average additional 0.609 (143%) to absolute sequential intraday jumps. This number of jumps is lower than found in the previous section, but the fewer jumps provide stronger reactions in absolute sequential jump sizes than both raw and standardised returns intraday jumps. The other statistically significant news items are Consumer Confidence and GDP Preliminary, although the numbers of jumps caused by these are low, whilst GDP Advance and Initial Claims correspond to 4 and 5 sequential intraday jumps respectively, though their impacts are not statistically significant. The effect of Bank of England interest rate announcements is no longer significant under the sequential intraday jump framework.

To complete the analysis of the equity index futures, Table 4.5.3.6 shows the regression results for DJ Euro Stoxx 50 futures. Of 310 sequential intraday jumps, 59 relate to news announcements, which add a statistically significant 0.306 (80.3%) to the average size of absolute sequential intraday jumps. The individual indicators of note are Consumer Confidence, GDP Advance, Initial Claims and Retail Sales, which show $N(D_{\delta,k}, \widetilde{\kappa}_k)$ values at five or above, and Business Inventories, CPI, ISM Index, and PPI, which provide both statistically significant coefficients and $N(D_{\delta,k}, \widetilde{\kappa}_k)$ values at five or above. The Employment Report is again the dominant indicator, in statistical and economic terms, with 16 out of a possible 89 announcements causing sequential intraday jumps and these jumps adding an average incremental 0.457 (110%) to average absolute sequential intraday jumps. Interestingly, a larger reaction in DJ Euro Stoxx 50 futures is derived from ECB interest rate announcements, raising the absolute value of sequential intraday jumps by 0.692 (160%) on average. This is a slightly larger reaction than shown in both raw and standardised returns intraday jumps in the previous section, however, this is based on only 2 occurrences of this announcement causing jumps.

Table 4.5.3.7 shows the results for the US 10-Year T-Bond futures, the first of the interest rate futures markets. The interesting feature in this market, for all news combined, is that the sequential method detects almost double the number of intraday jumps caused by news than the standardised returns intraday detection method of the previous section (142 compared to 77). As a proportion of total intraday jumps, this represents 27.5% (compared to 21.5%) of jumps caused by news announcements. In addition, this larger number of intraday jumps generates a marginally stronger impact on the absolute size of jumps since the estimated value of β_δ is larger for the sequential method. This demonstrates a more influential role for US macroeconomic news announcements in causing intraday jumps averaged over a larger number of announcements by the sequential method. The specifics of the data show that average absolute sequential intraday jumps are 0.184 (163%) larger when these important announcements occur. As with the results discussed above, there is a long list of individual indicators whose announcements are important for the US 10-Year T-Bond futures. Business Inventories, Chicago PMI, Construction Spending, Consumer Confidence, Factory Orders, Housing Starts, New Home Sales, New York Empire State Index and PPI, for example, all show values of $\mathrm{N}(D_{\delta,k}, \tilde{\kappa}_k)$ that are greater than or equal to 5, but these announcements do not generate statistically significant effects at the 5% level or lower on the average size of absolute intraday jumps. The statistically significant announcements displaying values of $\mathrm{N}(D_{\delta,k}, \tilde{\kappa}_k)$ greater than or equal to 5 are CPI, Employment Cost Index, GDP Advance, Initial Claims, ISM Index, Retail Sales, Employment Report and FOMC. The largest influences on jumps are provided by the Employment Report, Employment Cost Index, GDP Advance and FOMC, which increase the average level of absolute sequential intraday jumps by 0.394 (279%), 0.230 (144%), 0.203 (126%) and 0.160 (99.8%) respectively. There is clear evidence, therefore, that announcements relating to real activity, inflation and interest rates have powerful impacts on sequential intraday jumps in this market.

The UK Gilt futures market, shown in Table 4.5.3.8, exhibits a lower total number of sequential intraday jumps than the standardised returns intraday jump method of the previous section. Despite this, the proportion of these jumps corresponding to news is larger than that for standardised returns intraday jumps, and consistent with many of the other markets, is lower than the corresponding measure for raw returns intraday jumps. The estimated value of β_δ of 0.080 for the all news dummy variable also falls between the estimates for standardised and raw returns intraday jumps of the previous section, which is statistically significantly positive at the 1% level and corresponds economically to an increase in average absolute sequential intraday jumps of 59.3% at the times of these news announcements. Similar patterns are found for individual US macroeconomic news indicators. The interesting indicators are Consumer Confidence, CPI, Employment Cost Index, Initial Claims, PPI and Retail Sales, which display many instances of news causing jumps, but no statistically significant coefficients at standard levels. The more influential indicators are the ISM Index, Bank of England interest rate decisions and the Employment Report, the latter generating an average increase in the size of absolute jumps of 0.175 (126%).

The final market to consider is the Euro Bund futures market which is presented by Table 4.5.3.9. Similarly with the UK Gilt, the Bund market shows fewer total numbers of sequential jumps than the previous, stringent standardised returns intraday jumps, yet the sequential method shows a much larger proportion of these jumps being caused by news announcements, and a greater importance on news announcements in causing jumps, in absolute terms. The corresponding estimate for β_δ is not as high for sequential jumps, appearing to show news exerting a smaller average influence on the absolute size of jumps. Although relatively smaller, the value of 0.076 remains statistically significantly positive at the 1% level and represents a relative increase of 65.2% in the absolute size of jumps when these news announcements occur. Given that there is almost double the number of jumps caused by news for the sequential sample compared to the standardised returns intraday jumps series, it is perhaps not surprising that the inclusion of smaller jumps may dilute this impact on absolute jump size. Individually, there are many indicators showing correspondence with jumps and statistically significant increments to jump size and these support the findings above for the interest rate futures markets. Particularly noteworthy are Chicago PMI, Construction Spending, Consumer Confidence, CPI, Michigan Sentiment Preliminary, and Retail Sales. However, whilst causing numerous jumps, these do not increase the absolute jump size significantly at the 5% level or lower. The more influencial announcements are Business Inventories, Employment Cost Index, GDP Advance, Initial Claims, ISM Index, PPI, Employment Report and interest rate announcements by the Bank of England and European Central Bank. The largest influence is exerted by 25 of 95 announcements of the Employment Report, raising average absolute sequential intraday jumps by 0.173 (153%). GDP Advance also warrants mention with 10 of 32 possible announcements increasing average absolute intraday jumps by 0.068 in absolute terms, corresponding to 51.0% in relative terms.

To summarise briefly, the sequential method of intraday jump detection seems to offer a compromise between the raw and standardised returns intraday method of the previous section. Although the sequential procedure is more stringent, frequently finding fewer intraday jumps than the standardised returns intraday jumps method, the influence of US macroeconomic news on intraday jumps remains strong with higher proportions of these jumps caused by news. Statistically, news announcements exhibit a strong influence on the size of absolute sequential intraday jumps, an effect which is also significant in economic terms when the incremental increase in jump sizes caused by news is compared with the average size of the jumps not related to news announcements. The strength of this relationship and the proportions of jumps caused by news show that the sequential method includes more small jumps related to news that are eliminated by annihilating the intraday volatility pattern. Intraday jumps in the EUR-USD, S&P 500 E-Mini and interest rate futures markets are the most responsive to US macroeconomic news, with announcements regarding real activity, inflation and interest rates causing the more significant effects, while the Employment Report is dominant. These findings are entirely consistent with those of the previous section.

Tables 4.5.3.1 to 4.5.3.9 investigate the influence of macroeconomic news announcements on intraday jumps that are measured by the sequential method using $Z_{I,t}$ as the preferred daily jump test statistic, as described in section 4.4. To investigate the sensitivity of these results to the choice of daily jump test statistic, and to confirm the robustness of the results of this section and for completeness, Tables 4.5.3.10 to 4.5.3.18 show the regression results from a repetition of the investigation of the relationship between jumps and news for sequential intraday jumps detected using the alternative $U_{I,t}$ daily jump test statistic. Encouragingly, the results for each futures market shown in Tables 4.5.3.10 to 4.5.3.18 are remarkably similar to those of Tables 4.5.3.1 to 4.5.3.9 that use sequential intraday jumps identified using the $Z_{I,t}$ statistic. This shows very consistent, although not identical, measurement of significant intraday jumps by these alternative tests. Each market, except the Euro Bund, shows more sequential intraday jumps in total identified by the $U_{I,t}$ version of the test, higher numbers of jumps corresponding to all news announcements (α=0.001), lower proportions of jumps caused by news and lower estimated values of β_δ. These differences are very minor and certainly not large enough to alter the statistical or economic significance of the coefficient estimates. There are also some marginal changes in N($D_{\delta,k}$, $\widetilde{\kappa}_k$) and β_δ estimates for individual indicators, some of which cause changes in the statistical significance of parameters. However, the clear message of these tables is that there is very little difference in these results between the sequential jump measurement techniques. Also, the tables reinforce the strong and important relationship between intraday jumps, news announcements and economic fundamentals, emphasising the dramatic effect on jumps when US macroeconomic announcements (and occasionally UK and European interest rates decisions) are made, which is consistent across all markets considered here.

Although most of the differences in regression results between the $Z_{I,t}$ and $U_{I,t}$ versions of the test are minor, it is important, for completeness, to mention the notable cases. For EUR-USD futures, for example, comparison of Tables 4.5.3.1 and 4.5.3.10 shows a change in the statistical significance of the estimated values of β_δ for CPI, PPI and Trade Balance. The first two announcement coefficients are significantly greater than zero at the 5% level, whilst that for Trade Balance is statistically significantly positive at the 1% level for the $U_{I,t}$ version. Table 4.5.3.11 representing GBP-USD futures shows changes to the significance level of coefficients for Current Account (drop to 10%) and New Home Sales (rise to 1%) compared to Table 4.5.3.2, but these changes refer to only very few instances where jumps coincide with these announcements. Initial Claims, however, shows N($D_{\delta,k}$, $\widetilde{\kappa}_k$) rising from 7 to 9 with the subsequent fall in the estimate of β_δ altering its significance level from 5% to 10%. For JPY-USD in Table 4.5.3.12, there are slight changes in significance levels for rare, single announcements, but no substantive changes to the results.

Considering the equity markets, the results for the S&P 500 E-Mini futures market presented in Table 4.5.3.13 show very similar findings for the $U_{I,t}$ test compared to Table 4.5.3.4. The only minor discrepancies relate to Consumer Confidence and Leading Indicators which show increases in significance levels for estimated β_δ under the $U_{I,t}$ version of the test, even though there is no change in N($D_{\delta,k}$, $\widetilde{\kappa}_k$) for either indicator, but this significance is based on only single news announcements.

Table 4.5.3.10. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for EUR-USD Futures.

α		0.01 No. Jumps: 503		0.001 No. Jumps: 281		0.0001 No. Jumps: 177	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	1,840	113	**0.142****	83	**0.149****	63	**0.173****
Business Inventories	84	5	**0.051+**	5	0.022	3	0.036
Chicago PMI	82	5	-0.012	3	-0.035	3	-0.056
Construction Spending	88	5	0.026	3	0.010	2	-0.069
Consumer Confidence	89	11	**0.050+**	8	0.035	5	-0.025
CPI	88	5	**0.070***	4	**0.071***	3	0.051
Current Account	25	1	**0.052****	1	**0.023****	1	0.002
Employment Cost Index	30	4	0.079	1	**0.273****	1	**0.252****
Existing Home Sales	89	4	0.016	4	-0.013	3	-0.066
Factory Orders	86	4	0.006	3	-0.025	3	-0.047
GDP Advance	30	7	**0.145****	3	**0.283****	2	**0.368****
GDP Prel	27	1	**0.053****	1	**0.024****		
Housing Starts	89	2	-0.052	1	-0.086		
Initial Claims	378	20	**0.034+**	15	0.026	11	0.021
ISM Manufacturing	88	6	0.038	3	0.010	2	-0.069
Leading Indicators	90	2	-0.073	1	-0.149	1	-0.170
Mich Sentiment Prel	77	2	-0.054	1	-0.149	1	-0.170
New Home Sales	88	4	**0.122***	4	**0.093+**	1	**0.274****
NY Empire State Index	36	5	**0.059***	5	0.031	3	0.036
Non-Farm Payrolls	81	28	**0.290****	23	**0.278****	20	**0.302****
Personal Income	80	2	-0.028	2	-0.057	2	-0.078
Personal Spending	80	2	-0.028	2	-0.057	2	-0.078
PPI	83	6	**0.093***	5	**0.091***	5	**0.070+**
Productivity Prel	30	1	**0.102****	1	**0.074****	1	**0.053****
Productivity Rev	30	2	**0.023***				
Retail Sales	87	6	0.051	4	0.069	3	**0.094+**
Trade Balance	87	10	**0.129****	6	**0.176****	6	**0.157***
Unemployment Rate	81	28	**0.290****	23	**0.278****	20	**0.302****
FOMC	63	7	**0.120***	6	0.077	3	0.130

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in EUR-USD futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.11. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for GBP-USD Futures.

α		0.01 No. Jumps: 883		0.001 No. Jumps: 543		0.0001 No. Jumps: 380	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	1,950	94	**0.098****	62	**0.132****	49	**0.149****
Business Inventories	90	2	**0.135****	2	**0.128****	2	**0.120****
Chicago PMI	87	3	**0.049***	2	**0.066****	2	**0.058****
Construction Spending	94	6	0.012	4	0.012	2	-0.047
Consumer Confidence	95	6	**0.063****	5	**0.060***	4	**0.070****
CPI	94	4	**0.125****	4	**0.118****	4	**0.110****
Current Account	25	3	**0.017***	2	**0.015+**	2	0.007
Employment Cost Index	32	1	**0.068****				
Existing Home Sales	94	2	-0.012	2	-0.019	1	-0.030
Factory Orders	91	2	**0.052+**	1	0.097	1	**0.089****
GDP Advance	32	5	**0.148***	2	**0.211+**	1	**0.420****
GDP Final	31	1	-0.066				
Initial Claims	400	13	**0.036***	9	**0.037+**	8	**0.043***
ISM Manufacturing	94	6	0.012	4	0.012	2	-0.047
Leading Indicators	97	2	-0.021	1	-0.075	1	-0.083
Mich Sentiment Prel	82	3	-0.004	3	-0.011	1	-0.012
New Home Sales	93	2	0.049	1	**0.115****	1	**0.107****
NY Empire State Index	36	3	**0.097****	1	**0.174****	1	**0.166****
Non-Farm Payrolls	85	24	**0.196****	17	**0.255****	13	**0.304****
Personal Income	84	2	0.006	1	**0.070****	1	**0.062****
Personal Spending	84	2	0.006	1	**0.070****	1	**0.062****
PPI	89	7	0.014	3	**0.066+**	3	0.058
Productivity Prel	32	1	**0.009****	1	0.002	1	-0.006
Retail Sales	93	10	-0.002	4	0.011	4	0.002
Trade Balance	92	11	**0.115****	7	**0.168****	6	**0.182****
Unemployment Rate	85	24	**0.196****	17	**0.255****	13	**0.304****
FOMC	66	5	**0.065***	3	**0.114****	2	**0.065***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in GBP-USD futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.12. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for JPY-USD Futures.

α		0.01 No. Jumps: 556		0.001 No. Jumps: 328		0.0001 No. Jumps: 196	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	1951	51	**0.126****	32	**0.169****	24	**0.194****
Business Inventories	90	2	**0.066****	1	**0.084****	1	**0.056****
Chicago PMI	87	3	0.190	2	0.338	2	0.310
Construction Spending	94	1	-0.002				
Consumer Confidence	95	4	**0.035***	3	-0.001	1	-0.022
CPI	94	1	**0.102****	1	**0.084****	1	**0.056****
Current Account	25	1	**0.046****				
Employment Cost Index	32	1	-0.029				
Existing Home Sales	94	1	0.001	1	-0.017		
Factory Orders	91	1	**0.045****				
GDP Advance	32	1	-0.029				
Housing Starts	95	1	**0.008+**				
Initial Claims	401	10	-0.022	3	-0.026	1	-0.006
ISM Manufacturing	94	1	-0.002				
Mich Sentiment Rev	80	1	-0.059				
New Home Sales	93	2	**0.150****				
Non-Farm Payrolls	85	15	**0.275****	14	**0.272****	12	**0.269****
Personal Income	84	1	**0.073****	1	**0.055****	1	**0.026***
Personal Spending	84	1	**0.073****	1	**0.055****	1	**0.026***
PPI	89	5	0.039	1	**0.172****	1	**0.144****
Productivity Prel	32	1	-0.003				
Productivity Rev	32	1	-0.090				
Retail Sales	93	3	-0.019	2	-0.052	2	-0.081
Trade Balance	93	9	**0.106***	5	**0.139+**	3	**0.232***
Unemployment Rate	85	15	**0.275****	14	**0.272****	12	**0.269****
FOMC	66	4	0.015	3	-0.035	2	-0.058

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in JPY-USD futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.13. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for S&P 500 E-Mini Futures.

α		0.01 No. Jumps: 341		0.001 No. Jumps: 171		0.0001 No. Jumps: 88	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{\kappa}_k)$	β_δ
All News	2,135	72	**0.370****	54	**0.371****	37	**0.351***
Business Inventories	95	6	0.036	6	-0.065	4	-0.314
Chicago PMI	96	4	0.034	2	-0.071	1	-0.402
Construction Spending	94	3	0.064	2	-0.067	1	-0.006
Consumer Confidence	96	8	**0.205***	4	**0.252***	4	0.106
CPI	96	12	0.005	11	-0.086	7	-0.290
Employment Cost Index	32	2	**0.485***	1	**0.761****		
Existing Home Sales	96	1	-0.248	1	-0.347	1	-0.496
Factory Orders	95	3	-0.034	3	-0.135	2	-0.440
GDP Advance	32	2	**1.046****	2	**0.953****	1	**0.994****
GDP Prel	32	1	**0.179****	1	**0.081+**		
Housing Starts	96	3	-0.039	3	-0.140	2	-0.245
Initial Claims	413	6	0.158	4	0.127	2	-0.203
ISM Manufacturing	94	3	0.064	2	-0.067	1	-0.006
Leading Indicators	97	1	**0.238****	1	**0.140****	1	-0.006
Mich Sentiment Rev	95	1	-0.080				
New Home Sales	95	2	-0.060	1	-0.139	1	-0.286
NY Empire State Index	36	2	-0.146	2	-0.247	2	-0.398
Non-Farm Payrolls	93	21	**0.360****	17	**0.343****	12	**0.276+**
Personal Income	93	1	-0.273	1	-0.372		
Personal Spending	93	1	-0.273	1	-0.372		
PPI	95	4	0.005	2	-0.031	2	-0.179
Productivity Prel	31	2	-0.015	1	-0.207		
Retail Sales	95	4	**0.085***	4	-0.015	2	-0.116
Trade Balance	96	2	-0.101				
Unemployment Rate	93	21	**0.360****	17	**0.343****	12	**0.276+**
FOMC	67	5	**2.019****	4	**2.063***	4	**1.960***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in S&P 500 E-Mini futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{\kappa}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.14. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for FTSE 100 Futures.

α		0.01 No. Jumps: 456		0.001 No. Jumps: 226		0.0001 No. Jumps: 128	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	2,049	40	**0.213****	19	**0.196****	12	**0.210***
Business Inventories	92	1	-0.193	1	-0.231	1	-0.289
Construction Spending	88	1	-0.005	1	-0.043	1	-0.100
Consumer Confidence	93	2	**0.119****	1	**0.123****		
CPI	95	3	0.140	1	-0.231	1	-0.289
Employment Cost Index	32	3	**0.371***	2	0.193	2	0.137
GDP Advance	32	6	**0.255***	4	0.067	3	0.051
GDP Prel	32	2	**0.135****	1	**0.061****	1	0.004
Housing Starts	96	1	-0.117				
Initial Claims	406	7	**0.251****	5	0.140	4	0.133
ISM Manufacturing	87	1	-0.005	1	-0.043	1	-0.100
Mich Sentiment Prel	92	1	-0.212				
Mich Sentiment Rev	93	1	-0.172	1	-0.210		
NY Empire State Index	37	1	-0.193	1	-0.231	1	-0.289
Non-Farm Payrolls	94	14	**0.312****	7	**0.419****	4	**0.589****
Personal Income	89	1	**0.118****				
Personal Spending	89	1	**0.118****				
PPI	93	3	-0.017				
Productivity Prel	32	2	**0.186****	1	**0.056****	1	0.000
Retail Sales	94	2	**0.215****				
Trade Balance	95	1	**0.336****	1	**0.300****	1	**0.244****
Unemployment Rate	94	14	**0.312****	7	**0.419****	4	**0.589****
BOE	95	2	**0.146+**	1	**0.263****		
ECB	115	1	**0.449****				

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in FTSE 100 futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.15. Sequential Intraday Jumps ($U_{I,t}$) and News Dummy Variables for DJ Euro Stoxx 50 Futures.

α		0.01 No. Jumps: 604		0.001 No. Jumps: 323		0.0001 No. Jumps: 196	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	1,969	81	0.294**	61	0.319**	43	0.365**
Business Inventories	89	6	0.421**	6	0.392*	4	0.595**
Capacity Utilization	89	1	-0.160	1	-0.193	1	-0.240
Chicago PMI	86	4	-0.023	2	-0.183	1	-0.257
Construction Spending	84	5	0.239*	4	0.236+	2	0.480**
Consumer Confidence	88	7	0.100	5	0.127	2	0.173
CPI	90	7	0.205+	6	0.220+	4	0.205
Employment Cost Index	30	3	0.185+	2	0.066	1	0.218**
Factory Orders	89	3	0.248	2	0.344	1	0.778**
GDP Advance	30	6	0.154*	5	0.081	2	-0.012
GDP Final	30	1	-0.205				
GDP Prel	30	3	0.109	3	0.077	3	0.030
Housing Starts	90	4	0.102	2	0.118	1	-0.280
Industrial Production	89	1	-0.160	1	-0.193	1	-0.240
Initial Claims	382	12	0.148*	9	0.121+	6	0.068
ISM Manufacturing	83	7	0.258*	6	0.249+	2	0.480**
Leading Indicators	89	2	0.217**	1	0.275**	1	0.229**
Mich Sentiment Prel	89	1	0.069**	1	0.037*	1	-0.009
Mich Sentiment Rev	89	2	-0.053	2	-0.086	1	-0.241
New Home Sales	90	3	-0.045				
NY Empire State Index	37	2	-0.073	2	-0.106		
Non-Farm Payrolls	89	21	0.463**	16	0.484**	15	0.481**
Personal Income	88	1	0.176**				
Personal Spending	88	1	0.176**				
PPI	88	6	0.449**	4	0.512**	3	0.654**
Productivity Prel	29	4	0.213**	4	0.181**	2	0.189+
Productivity Rev	30	3	0.050	2	0.046		
Retail Sales	89	8	0.137+	5	0.129	4	0.098
Trade Balance	90	1	0.131**	1	0.099**	1	0.052*
Unemployment Rate	89	21	0.463**	16	0.484**	15	0.481**
ECB	116	2	0.747**	2	0.716**	2	0.672**

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in DJ Euro Stoxx 50 futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{I,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.16. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for US 10-Year T-Bond Futures.

α		0.01 No. Jumps: 868		0.001 No. Jumps: 528		0.0001 No. Jumps: 364	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	1,903	205	**0.160****	142	**0.172****	110	**0.177****
Business Inventories	87	12	**0.118***	10	**0.081***	6	**0.117***
Capacity Utilization	87	8	0.005	1	-0.032	1	-0.050
Chicago PMI	86	8	**0.056***	7	0.043	6	0.009
Construction Spending	93	20	**0.060****	12	0.023	10	-0.003
Consumer Confidence	95	13	0.033	8	0.022	6	0.033
CPI	94	20	**0.142****	17	**0.109****	15	**0.099****
Current Account	25	2	**0.103***	2	**0.085***	2	**0.068+**
Employment Cost Index	32	9	**0.217****	7	**0.259****	6	**0.271****
Existing Home Sales	94	7	-0.002	3	-0.015	1	-0.110
Factory Orders	90	11	0.004	6	0.008	6	-0.010
GDP Advance	32	10	**0.187****	7	**0.228****	6	**0.235****
GDP Final	31	2	-0.006				
GDP Prel	29	4	0.008	2	0.031	2	0.014
Housing Starts	95	9	**0.064****	6	0.040	6	0.023
Industrial Production	87	8	0.005	1	-0.032	1	-0.050
Initial Claims	393	36	**0.082****	29	**0.090****	21	**0.098****
ISM Manufacturing	92	21	**0.084****	12	**0.032+**	10	0.007
Leading Indicators	96	4	**0.093***	3	0.040	3	0.023
Mich Sentiment Prel	77	3	-0.010	2	-0.012	1	-0.092
Mich Sentiment Rev	73	2	**0.150****	2	**0.133****	1	**0.110****
New Home Sales	88	9	**0.054***	7	0.032	5	0.032
NY Empire State Index	36	7	**0.111***	6	**0.084+**	4	**0.129***
Non-Farm Payrolls	80	30	**0.397****	26	**0.393****	19	**0.428****
Personal Income	81	3	**0.116****	2	**0.090***	2	**0.073+**
Personal Spending	81	3	**0.116****	2	**0.090***	2	**0.073+**
PPI	84	13	**0.062***	11	**0.055***	7	**0.065+**
Productivity Prel	32	4	**0.095***	3	0.057	2	**0.100***
Retail Sales	91	26	**0.096****	20	**0.094****	16	**0.087****
Trade Balance	90	4	0.049	2	0.080	2	0.063
Treasury Budget	86	1	-0.112				
Unemployment Rate	80	30	**0.397****	26	**0.393****	19	**0.428****
FOMC	66	11	**0.224****	8	**0.163***	5	**0.230***

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in US 10-Year T-Bond futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.17. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for UK Gilt Futures.

α		0.01 No. Jumps: 982		0.001 No. Jumps: 589		0.0001 No. Jumps: 373	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	2,034	103	**0.073****	74	**0.075****	51	**0.089****
Business Inventories	92	4	**0.074+**	2	**0.136***	2	0.123
Capacity Utilization	94	2	-0.045	2	-0.058	1	-0.064
Chicago PMI	90	5	0.003	4	-0.011	2	-0.025
Construction Spending	87	5	**0.038+**	2	**0.041***	2	0.028
Consumer Confidence	91	9	0.008	6	0.021	5	0.016
CPI	95	7	**0.076***	4	**0.110+**	3	**0.135***
Current Account	25	1	-0.043				
Employment Cost Index	32	6	**0.094****	5	**0.068+**	5	0.055
Existing Home Sales	90	1	-0.040				
Factory Orders	96	5	-0.016	4	-0.018	2	0.015
GDP Advance	32	7	**0.099****	6	**0.076***	5	**0.064+**
GDP Final	31	1	-0.008				
Housing Starts	96	1	0.274	1	**0.261****	1	**0.248****
Industrial Production	94	2	-0.045	2	-0.058	1	-0.064
Initial Claims	401	11	**0.056***	8	0.043	6	**0.055+**
ISM Manufacturing	86	8	**0.054****	4	**0.050****	3	**0.035***
Leading Indicators	94	2	**0.043+**	1	**0.072****	1	**0.058****
Mich Sentiment Prel	91	5	0.010	3	-0.023	2	-0.009
Mich Sentiment Rev	92	1	**0.023****	1	**0.011****	1	-0.002
New Home Sales	88	3	-0.041	1	-0.068		
NY Empire State Index	37	3	**0.086+**	2	**0.136***	2	**0.123***
Non-Farm Payrolls	93	25	**0.191****	21	**0.187****	16	**0.204****
Personal Income	87	1	-0.014				
Personal Spending	87	1	-0.014				
PPI	92	8	**0.024+**	6	0.009	4	-0.013
Productivity Prel	31	2	**0.149****	2	**0.137****	2	**0.123****
Productivity Rev	32	1	**0.085****	1	**0.073****	1	**0.059****
Retail Sales	93	10	-0.001	6	-0.031	4	-0.034
Trade Balance	93	1	**0.032****				
Unemployment Rate	93	25	**0.191****	21	**0.187****	16	**0.204****
BOE	94	5	**0.054****	4	**0.046****	2	**0.026****

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in UK Gilt futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

Table 4.5.3.18. Sequential Intraday Jumps ($U_{1,t}$) and News Dummy Variables for Euro Bund Futures.

α		0.01 No. Jumps: 703		0.001 No. Jumps: 393		0.0001 No. Jumps: 248	
	$N(D_{\delta,k})$	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ	$N(D_{\delta,k}, \widetilde{K}_k)$	β_δ
All News	2,095	144	**0.070****	92	**0.083****	71	**0.086****
Business Inventories	95	6	**0.104***	4	**0.115***	4	**0.098+**
Capacity Utilization	95	7	-0.026	1	-0.060	1	-0.078
Chicago PMI	89	8	0.014	5	-0.009	5	-0.027
Construction Spending	90	10	**0.043***	4	**0.036+**	2	**0.062***
Consumer Confidence	93	9	0.007	6	0.011	3	-0.057
CPI	96	10	**0.031+**	5	**0.048+**	4	0.029
Current Account	25	1	**0.011****	1	-0.005		
Employment Cost Index	32	9	**0.095****	8	**0.073****	7	**0.065****
Existing Home Sales	93	3	-0.020	1	-0.064		
Factory Orders	95	4	-0.002	3	-0.029	3	-0.047
GDP Advance	32	10	**0.090****	8	**0.073****	7	**0.066****
GDP Final	32	3	-0.017	1	-0.059		
GDP Prel	32	1	-0.019				
Housing Starts	96	5	0.009	2	0.019	1	-0.035
Industrial Production	95	7	-0.026	1	-0.060	1	-0.078
Initial Claims	405	27	**0.030***	15	**0.048****	13	**0.038***
ISM Manufacturing	90	13	**0.061****	7	**0.065****	4	**0.078****
Leading Indicators	95	1	**0.098****				
Mich Sentiment Prel	94	8	-0.001	5	0.003	4	0.001
Mich Sentiment Rev	93	3	0.027	1	**0.117****	1	**0.099****
New Home Sales	93	5	-0.016	2	-0.055	2	-0.073
NY Empire State Index	37	5	0.005	3	-0.010	3	-0.028
Non-Farm Payrolls	95	28	**0.171****	23	**0.171****	19	**0.196****
Personal Income	93	2	-0.036	2	-0.052	1	-0.033
Personal Spending	93	2	-0.036	2	-0.052	1	-0.033
PPI	94	9	**0.093****	7	**0.090****	6	**0.078***
Productivity Prel	31	3	0.047	2	**0.089****	2	**0.071****
Retail Sales	95	14	**0.036***	10	0.038	5	0.014
Trade Balance	96	3	0.015	1	**0.042****	1	**0.025****
Unemployment Rate	95	28	**0.171****	23	**0.171****	19	**0.196****
BOE	97	1	**0.067****	1	**0.051****	1	**0.033****
ECB	118	3	**0.105****	2	**0.065****	2	**0.047****

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in Euro Bund futures returns. Intraday jumps are detected by the sequential method according to equations (4.37) and (4.38) using the $U_{1,t}$ test statistic for daily jump measurement and across a range of significance levels (α). N($D_{\delta,k}$) measures the number of each macroeconomic announcement within the sample and N($D_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with each macroeconomic news indicator. Only those announcements with at least one coincidence of news and jumps are displayed and All News refers to the combination of all separate announcements into one variable. Finally, β_δ reports the estimated coefficient from equation (4.42) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a one-tailed test against the null that β_δ=0. Each regression uses all available intraday jumps.

More interesting are the changes to coefficients for the Employment Report and FOMC decisions, the two most influencial announcements for S&P 500 E-Mini futures jumps. For the $U_{I,t}$ version of sequential intraday jumps, there are 2 more instances of jumps caused by Employment Report announcements compared to the $Z_{I,t}$ version and this has the effect of increasing estimated β_δ to 0.343 suggesting that these announcements increase the average absolute size of sequential jumps by 67.6% in relative terms (compared with 42.2% for the $Z_{I,t}$ version). For FOMC decisions, one less announcement coinciding with jumps causes the β_δ estimate to increase to 2.063 in Table 4.5.3.13, such that these few important announcements increase absolute sequential intraday jumps by a monumental 418% on average. The opposite of this effect for the Employment Report is observed for FTSE 100 futures in Table 4.5.3.14. An additional 2 instances of its announcement cause jumps for the $U_{I,t}$ version, but these reduce the estimate of β_δ from 0.609 in Table 4.5.3.5 to 0.419 in Table 4.5.3.14. Whilst it remains statistically positive at the 1% level, this change implies that these announcements of the Employment Report contribute 109% to the average size of absolute sequential intraday jumps (compared to 144% for $Z_{I,t}$) in economic terms. It is also noticeable that a single Bank of England announcement generates a statistically significant rise in the intraday jump for this interval of 0.263 (66.1%) for the $U_{I,t}$ version only. For the DJ Euro Stoxx 50 futures in Tables 4.5.3.15 and 4.5.3.6, there are slight decreases in statistical significance for coefficients, for the $U_{I,t}$ version of the test, on Business Inventories, CPI and ISM Index and a slight increase for Factory Orders, but otherwise the figures remain very consistent between the two tables. The largest difference between the two tables is for the Employment Report, where 5 fewer instances of jumps coinciding with news are found for the $U_{I,t}$ version causing a slight fall in the estimated value of β_δ, but no change in its statistical significance. The effect of these announcements on intraday jumps remains statistically significant at the 1% level, and increases the average size of absolute sequential intraday jumps by 0.431% and 108% in absolute and relative terms respectively.

To complete the analysis, the interest rate futures contracts are shown in Tables 4.5.3.16 to 4.5.3.18. The $U_{I,t}$ version causes slight changes in $N(D_{\delta,k}, \widetilde{\kappa}_k)$ and β_δ estimates for individual indicators in the US 10-Year T-Bond futures in table 4.5.3.16 compared to the $Z_{I,t}$ version of Table 4.5.3.7. Slight changes in these measures for CPI, Employment Cost Index, GDP Advance, Initial claims and the Employment Report do not alter statistical significance, whereas coefficient significance is enhanced for Business Inventories and PPI, but is less strong for the ISM Index. Consistent with the results of previous sections, the results for US 10-Year T-Bond futures market in Table 4.5.3.18 show that it is the most responsive market to US macroeconomic news announcements in terms of the number of announcements coinciding with jumps. Tables 4.5.3.17 and 4.5.3.8 confirm the consistency of jump measurement between the $U_{I,t}$ and $Z_{I,t}$ versions of the sequential intraday jump test for UK Gilt futures. Results are remarkably similar between the two tables with only minor changes to Construction Spending and the New York Empire State Index, the former increasing in significance to the 5% level and the latter falling to that same significance level. The single influencial announcement of the Trade Balance in Table 4.5.3.8 is not identified as an intraday jump by the $U_{I,t}$ version of the test and the other important difference surrounds the Employment Report. Four fewer announcements cause jumps for the $U_{I,t}$ version, which causes β_δ to increase such that the remaining announcements increase the average size of absolute sequential intraday jumps by 0.187, corresponding to an increase of 141% in relative terms. The Euro Bund futures market is slightly different since it shows the identical total number of jumps under both the $U_{I,t}$ and $Z_{I,t}$ versions of the test in Tables 4.5.3.18 and 4.5.3.9. These jumps have fewer instances of jumps relating to news for $U_{I,t}$, showing that at least some different jumps are identified by the two methods. Contrary to other makets, the estimate of β_δ for all news is higher for the $U_{I,t}$ version than the $Z_{I,t}$ statistic, the former indicating that news announcements increase average absolute intraday jumps by 0.083 or 75.3%. In terms of the individual announcements, there are very few differences in results between Tables 4.5.3.18 and 4.5.3.9. The important changes relate to Initial Claims, ISM Index and PPI, which have their coefficients increase in significance level from 5% to 1% for the $U_{I,t}$ version of the test. Results for the Employment Report are almost identical, whilst GDP Advance has 2 fewer N($D_{\delta,k}$, $\widetilde{\kappa}_k$) and a higher β_δ estimate for $U_{I,t}$, and these announcents correspond to an increase in the absolute size of sequential intraday jumps of 0.073 (56.9%).

To conclude this section, the sequential intraday jump methodology shows extremely strong consistency between the alternative $Z_{I,t}$ and $U_{I,t}$ versions of the test.

The regression results in Tables 4.5.3.1 to 4.5.3.18 confirm the dramatic influence of US macroeconomic announcements in causing many jumps and contributing significantly to their size. These findings correlate strongly with those of section 4.5.2 that use the alternative raw and standardised returns intraday jump detection procedure. Whilst the raw returns show larger numbers of jumps caused by news, the standardised returns reveal fewer announcements that impact far more strongly on the size of jumps. This suggests that annihilating the intraday volatility pattern that is inherent in high frequency returns removes many small intraday jumps to leave smaller numbers of jumps that show a more marked increase in jump size when coinciding with important news announcements. In comparison, the results of this section suggest that the sequential method appears to offer an alternative to these two. Despite this interesting variation across methodologies, the more important findings of these results show the dramatic role of macroeconomic news announcements in causing intraday jumps. Whilst the previous empirical literature has shown maroeconomic news to influence five-minute returns, this is the first known study to investigate this influence on those returns classified as intraday jumps. News announcements related to macroeconomic fundamentals, therefore, are a crucial determinant of the timing and size of jumps. Intraday jumps in interest rate futures markets, and the US 10-Year T-Bond futures in particular, are especially responsive to news announcements, along with the EUR-USD and S&P 500 E-Mini futures markets. The Employment Report is by far the most important announcement for all markets considered, frequently doubling the average size of intraday jumps across a number of announcements. Interest rate decisions and announcements of news relating to the real economy and inflation are also important. It is to these important indicators that the attention of the remainder of this chaper turns by investigating the effect and influence of the news information contained in these releases. Sp.

4.5.4 Intraday Jumps and Standardised News

In extension of the previous section's evidence that news announcements have significant impacts on intraday jumps, this final analysis investigates the relationship between the information surprise of news releases and intraday jumps. Specifically, intraday jumps are regressed on a standardised news measure for individual indicator δ according to:

$$\kappa_k = \varpi_\delta + \gamma_\delta S_{\delta,k} + \xi_{\delta,k}, \tag{4.43}$$

where $S_{\delta,k}$ is measured as $\left(A_{\delta,k} - E_{\delta,k}\right)/\sigma_{\delta,k}$, the deviation of the actual announcement, $A_{\delta,k}$, from its expected value, $E_{\delta,k}$, standardised by the sample standard deviation of this deviation, $\sigma_{\delta,k}$.[31] Regressions use only those intraday jumps that correspond to the relevant news announcements, provided there are at least five such coincidences. Although this is an arbitrary selection, it is made to emphasise the more systematic relationships between jumps and news rather than reactions to single events. Tables 4.5.4.1 to 4.5.4.9 display $N(S_{\delta,k}, \kappa_k)$, measuring the number of occurrences of news coinciding with jumps and hence the number of observations in the regression, estimates of γ_δ and R^2 measures of these regressions. Panel (A) displays the results for intraday jumps detected using raw returns whilst panel (B) shows the results for those jumps detected using standardised returns, and both panels compare the results for jumps detected at conservative levels of α of 0.001 and 0.0001.

The general findings that emerge from the tables are as follows. First, there are many coefficients that are significantly different from zero showing that the informational surprises from the releases of many different individual indicators exhibit an important influence on jumps. Those indicators showing significant coefficient estimates also show very large values of R^2 for the regression showing that the surprise content of news releases explains large proportions of the sizes of intraday jumps. In comparison with results reported by Andersen, Bollerslev, Diebold and Vega (2003, 2007), which are based on simiar regressions of returns on standardised news, the coefficient estimates and R^2 measures reported here are much larger. Of course this may be due to the different samples used, but is more likely the result of the use of only the largest returns that are identified as intraday jumps. This evidence, therefore, emphasises the role of US macroeconomic news surprises in causing dramatic returns that are classified as intraday jumps.

[31] The actual and expected announcemement data are retrieved from Briefing.com for this chapter, where the market expectation figure represents the median expectation of a survey of leading economists. Interest Rate expectations are derived from the closing prices of short term interest rate futures on the days prior to announcements.

Table 4.5.4.1. Intraday Jumps and Standardised News for EUR-USD Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 571			No. Jumps: 357		
Business Inventories	6	0.223	0.188	6	0.223	0.188
Chicago PMI	6	**-0.193+**	0.518			
Construction Spending	9	-0.496	0.229	7	**-0.896****	0.616
Consumer Confidence	16	**-0.188****	0.759	9	**-0.204****	0.887
CPI	8	-0.063	0.035	7	0.214	0.058
Existing Home Sales	5	0.025	0.020			
GDP Advance	9	**-0.291***	0.682	6	**-0.373***	0.739
Initial Claims	26	0.030	0.011	18	0.138	0.152
ISM Manufacturing	11	**-0.172****	0.500	9	**-0.180****	0.504
New Home Sales	7	**-0.112****	0.323			
NY Empire State Index	6	-0.127	0.169	5	-0.092	0.101
Non-Farm Payrolls	38	**-0.349****	0.494	34	**-0.359****	0.495
PPI	15	0.038	0.022	12	**0.116+**	0.137
Retail Sales	16	**-0.663+**	0.350	13	**-0.658+**	0.357
Trade Balance	18	**-0.209****	0.724	13	**-0.201****	0.725
Unemployment Rate	38	**0.161***	0.106	34	**0.177****	0.126
FOMC	12	-0.174	0.051	10	-0.129	0.025
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 462			No. Jumps: 272		
Non-Farm Payrolls	15	**-0.645****	0.794	12	**-0.729****	0.868
Unemployment Rate	15	0.180	0.085	12	0.182	0.096
FOMC	15	-0.017	0.001	11	-0.124	0.023

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in EUR-USD futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.2. Intraday Jumps and Standardised News for GBP-USD Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 592			No. Jumps: 350		
Construction Spending	5	**-0.581***	0.532			
Consumer Confidence	7	**-0.148****	0.856	6	**-0.147****	0.844
CPI	7	0.123	0.107			
GDP Advance	7	**-0.269***	0.738	5	**-0.272+**	0.744
Initial Claims	16	0.110	0.232	10	0.091	0.170
ISM Manufacturing	6	**-0.120****	0.628			
Non-Farm Payrolls	27	**-0.392****	0.702	24	**-0.403****	0.725
PPI	6	0.277	0.167	5	0.296	0.203
Retail Sales	8	**-1.532****	0.808			
Trade Balance	14	**-0.155****	0.689	11	**-0.154****	0.671
Unemployment Rate	27	0.082	0.058	24	0.097	0.059
FOMC	7	-0.130	0.175			
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 564			No. Jumps: 331		
Non-Farm Payrolls	9	**-0.378****	0.863	9	**-0.378****	0.863
Unemployment Rate	9	0.006	0.000	9	0.006	0.000
FOMC	10	**-0.130+**	0.179	9	-0.160	0.173

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in GBP-USD futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.3. Intraday Jumps and Standardised News for JPY-USD Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
		No. Jumps: 522			No. Jumps: 300	
Consumer Confidence	6	-0.091	0.298			
Initial Claims	12	0.130	0.159	7	**0.274****	0.808
Non-Farm Payrolls	25	**-0.247****	0.378	21	**-0.262****	0.434
Retail Sales	6	**-1.290***	0.635			
Trade Balance	10	**-0.162****	0.642	7	**-0.157***	0.608
Unemployment Rate	25	0.067	0.030	21	0.060	0.024
FOMC	5	-0.109	0.218	5	-0.109	0.218
(B) Intraday Jumps using Standardised Returns						
		No. Jumps: 428			No. Jumps: 230	
Non-Farm Payrolls	13	**-0.266+**	0.471	11	**-0.265+**	0.472
Unemployment Rate	13	**0.157+**	0.174	11	**0.258***	0.233
FOMC	8	**-0.114***	0.172	5	-0.109	0.218

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in JPY-USD futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.4. Intraday Jumps and Standardised News for S&P 500 E-Mini Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 365			No. Jumps: 190		
Business Inventories	8	0.010	0.000	8	0.010	0.000
Chicago PMI	8	0.257	0.108			
Construction Spending	9	**0.304***	0.499			
Consumer Confidence	11	**0.256****	0.511	7	0.113	0.257
CPI	12	0.013	0.001	11	0.017	0.002
Factory Orders	5	0.082	0.025			
GDP Advance	5	0.129	0.012			
Initial Claims	11	0.111	0.045	9	-0.027	0.001
ISM Manufacturing	10	0.137	0.071			
Non-Farm Payrolls	27	0.202	0.082	22	0.208	0.081
PPI	7	-0.446	0.265			
Productivity Prel	5	-0.025	0.008			
Retail Sales	10	-0.760	0.015	6	-3.065	0.251
Unemployment Rate	27	-0.158	0.041	22	-0.167	0.050
FOMC	10	**-0.741****	0.297	10	**-0.741****	0.297
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 299			No. Jumps: 187		
Business Inventories	5	0.034	0.017			
CPI	8	-0.053	0.024	6	-0.198	0.136
Initial Claims	6	0.017	0.001			
Non-Farm Payrolls	17	0.181	0.043	10	-0.040	0.001
Unemployment Rate	17	-0.199	0.069	10	-0.284	0.096
FOMC	10	**-0.741****	0.297	10	**-0.741****	0.297

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in S&P 500 E-Mini futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.5. Intraday Jumps and Standardised News for FTSE 100 Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 447			No. Jumps: 264		
Consumer Confidence	11	**0.272****	0.375	8	**0.195***	0.647
GDP Advance	5	**0.582+**	0.334			
Initial Claims	12	-0.224	0.053	8	-0.189	0.043
Non-Farm Payrolls	18	0.134	0.038	15	0.096	0.017
Unemployment Rate	18	-0.154	0.044	15	-0.235	0.084
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 447			No. Jumps: 264		
Non-Farm Payrolls	8	0.081	0.005	7	0.526	0.137
Unemployment Rate	8	-0.406	0.192	7	-0.365	0.167

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in FTSE 100 futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.6. Intraday Jumps and Standardised News for DJ Euro Stoxx 50 Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 463			No. Jumps: 279		
Business Inventories	6	0.103	0.008	5	0.299	0.052
Chicago PMI	8	0.389	0.410	6	**0.543****	0.880
Construction Spending	9	**0.292+**	0.216	6	0.249	0.120
Consumer Confidence	15	**0.436****	0.462	10	**0.408****	0.729
CPI	8	-0.130	0.045	6	-0.261	0.159
Employment Cost Index	5	**-0.496+**	0.548			
GDP Advance	11	**0.866****	0.701	7	**0.902****	0.759
Initial Claims	16	**-0.552****	0.294	12	**-0.508+**	0.212
ISM Manufacturing	12	**0.438****	0.536	9	**0.476****	0.660
Non-Farm Payrolls	25	0.188	0.041	24	0.247	0.060
PPI	6	-0.379	0.138			
Productivity Prel	6	**0.551****	0.801			
Retail Sales	11	1.271	0.049	9	1.453	0.079
Unemployment Rate	25	-0.237	0.067	24	-0.236	0.066
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 293			No. Jumps: 170		
Initial Claims	5	-0.082	0.000			
Non-Farm Payrolls	12	0.268	0.041	7	0.216	0.009
Unemployment Rate	12	-0.310	0.079	7	-0.274	0.058

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in DJ Euro Stoxx 50 futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.7. Intraday Jumps and Standardised News for US 10-Year T-Bond Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 596			No. Jumps: 419		
Business Inventories	15	0.065	0.058	13	0.077	0.069
Capacity Utilization	7	**-0.126****	0.837	6	**-0.123****	0.907
Chicago PMI	14	**-0.157****	0.399	10	**-0.206****	0.752
Construction Spending	26	-0.019	0.005	21	0.003	0.000
Consumer Confidence	18	**-0.130****	0.676	12	**-0.143****	0.776
CPI	28	-0.049	0.049	22	-0.065	0.075
Employment Cost Index	8	**-0.288***	0.388	8	**-0.288***	0.388
Existing Home Sales	5	-0.141	0.379			
Factory Orders	9	**-0.060***	0.550	7	**-0.108***	0.629
GDP Advance	14	**-0.226****	0.453	12	**-0.225***	0.454
Housing Starts	11	0.017	0.007	9	0.101	0.130
Industrial Production	7	**-0.114****	0.793	6	**-0.116****	0.919
Initial Claims	44	**0.070***	0.142	36	**0.074***	0.138
ISM Manufacturing	28	**-0.155****	0.498	23	**-0.154****	0.527
Mich Sentiment Prel	6	-0.118	0.440			
New Home Sales	10	**-0.119****	0.458	7	**-0.107***	0.475
NY Empire State Index	10	-0.076	0.139	8	-0.099	0.104
Non-Farm Payrolls	43	**-0.361****	0.443	40	**-0.369****	0.461
Personal Income	5	-0.163	0.173	5	-0.163	0.173
Personal Spending	5	**-0.282+**	0.688	5	**-0.282+**	0.688
PPI	17	**-0.086***	0.180	17	**-0.086***	0.180
Retail Sales	34	**-0.606***	0.205	31	**-0.619***	0.219
Unemployment Rate	43	**0.151***	0.090	40	**0.169***	0.103
FOMC	24	-0.083	0.045	22	-0.082	0.047
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 358			No. Jumps: 235		
Capacity Utilization	7	**-0.126****	0.837	6	**-0.123****	0.907
Construction Spending	6	**0.050+**	0.578			
CPI	5	-0.051	0.025			
Industrial Production	7	**-0.114****	0.793	6	**-0.116****	0.919
ISM Manufacturing	7	-0.009	0.006	5	-0.012	0.010
Mich Sentiment Prel	6	-0.118	0.440			
Non-Farm Payrolls	15	**-0.608****	0.801	12	**-0.596****	0.787
Unemployment Rate	15	-0.015	0.000	12	-0.393	0.137
FOMC	23	-0.081	0.046	20	-0.105	0.065

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in US 10-Year T-Bond futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.8. Intraday Jumps and Standardised News for UK Gilt Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 880			No. Jumps: 581		
Business Inventories	5	0.035	0.008			
Chicago PMI	9	**-0.120****	0.752	8	**-0.122****	0.773
Construction Spending	8	**-0.081****	0.179	6	-0.103	0.100
Consumer Confidence	9	**-0.102****	0.746	5	**-0.120***	0.721
CPI	13	**-0.105****	0.396	10	**-0.104***	0.373
Employment Cost Index	7	-0.027	0.003	6	-0.021	0.002
GDP Advance	10	**-0.183****	0.643	8	**-0.203****	0.631
Initial Claims	14	**0.137+**	0.170	12	0.130	0.157
ISM Manufacturing	11	**-0.085***	0.432	9	**-0.083***	0.394
Mich Sentiment Prel	7	**-0.088****	0.892			
Non-Farm Payrolls	34	**-0.191****	0.371	32	**-0.245****	0.468
PPI	13	-0.046	0.081	9	-0.028	0.029
Retail Sales	19	**-0.449***	0.376	15	**-0.437***	0.396
Unemployment Rate	34	**0.101****	0.142	32	**0.101****	0.141
BOE	10	-0.013	0.006	8	-0.017	0.006
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 674			No. Jumps: 421		
Non-Farm Payrolls	19	**-0.279****	0.537	17	**-0.280****	0.545
Unemployment Rate	19	**0.123***	0.144	17	**0.129+**	0.155
BOE	10	-0.013	0.006	10	-0.013	0.006

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in UK Gilt futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.4.9. Intraday Jumps and Standardised News for Euro Bund Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2	$N(S_{\delta,k}, \kappa_k)$	γ_δ	R^2
(A) Intraday Jumps using Raw Returns						
	No. Jumps: 790			No. Jumps: 534		
Business Inventories	9	0.051	0.116	7	0.027	0.031
Capacity Utilization	5	-0.048	0.258			
Chicago PMI	12	**-0.111****	0.689	10	**-0.115****	0.698
Construction Spending	18	-0.006	0.001	14	0.003	0.000
Consumer Confidence	10	**-0.104****	0.707	8	**-0.099****	0.654
CPI	18	**-0.058+**	0.165	14	**-0.059+**	0.175
Employment Cost Index	9	-0.077	0.079	9	-0.077	0.079
Factory Orders	9	-0.056	0.122	7	**-0.157***	0.541
GDP Advance	14	**-0.173****	0.745	14	**-0.173****	0.745
Industrial Production	5	-0.044	0.239			
Initial Claims	30	0.034	0.040	23	0.011	0.004
ISM Manufacturing	21	**-0.091****	0.523	17	**-0.095****	0.480
Mich Sentiment Prel	12	**-0.094****	0.768	6	**-0.092+**	0.684
New Home Sales	7	-0.042	0.180	5	-0.026	0.073
NY Empire State Index	6	-0.041	0.220			
Non-Farm Payrolls	44	**-0.179****	0.330	35	**-0.184****	0.337
PPI	15	-0.028	0.023	11	-0.038	0.039
Retail Sales	24	**-0.015***	0.038	20	**-0.417****	0.389
Unemployment Rate	44	**0.093****	0.133	35	**0.103***	0.140
ECB	5	-0.043	0.078	5	-0.043	0.078
(B) Intraday Jumps using Standardised Returns						
	No. Jumps: 539			No. Jumps: 339		
Mich Sentiment Prel	6	**-0.092+**	0.684	5	**-0.092+**	0.680
Non-Farm Payrolls	17	**-0.315****	0.552	14	**-0.363****	0.712
Unemployment Rate	17	**0.134***	0.180	14	**0.129+**	0.154
ECB	7	-0.064	0.167	6	-0.054	0.103

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in Euro Bund futures returns. Intraday jumps are detected according to equation (4.36) across a range of significance levels (α). $N(S_{\delta,k}, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.43) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

The second general finding from the tables is that the indicators showing significant coefficient estimates are different to those identified using simple dummies in the previous sections. This may suggest that indicators cause different responses in prices, some causing jumps due to pure announcement effects and others casuing jumps that are related to the informational surprise contained in the data release. Also, some indicators are important in both types of regression, using dummie and news variables. Third, the results in Tables 4.5.4.1 to 4.5.1.9 are very consistent across the significance levels of the jump detection procedure. By reducing the level of α from 0.001 to 0.0001, many indicators remain significant, often with larger coefficient estimates in absolute terms and larger measures of R^2. Fourth, consistent with the findings of the previous sections, the interest rate futures markets are most responsive to macroeconomic news in terms of the number of jumps caused by news, the number of indicators showing significant coefficients and the high values of R^2. In contrast, equity index futures in the US and UK show little reaction to news innovations, despite the strong impact found for announcement dummies. Finally, standardising returns to remove the intraday volatility pattern reduces the number of jumps detected and therefore the number of jumps caused by news. However, the few indicators that show significant responses to news tend to have very large coefficient estimates and R^2 measures, showing that the larger jumps identified are more strongly related to news with this news explaining larger proportions of the jumps.

Table 4.5.4.1 shows the results for EUR-USD futures where Chicago PMI, Consumer Confidence, GDP Advance, ISM Index, New Home Sales, Non Farm Payrolls, Retail Sales, Trade Balance and the Unemployment Rate are the important significant indicators. This list is quite different to that from Table 4.5.2.1 for the simple dummy variables. Since the contract is priced as USD per EUR, the signs of these significant coefficients reveal a strengthening of USD in response to unexpectedly positive news about the US macroeconomy. R^2 values are very large for these announcements, often above 0.5, and are particularly large for Consumer Confidence and Trade Balance. Coefficients are also large in absolute terms and with the exception of Retail Sales, which is significant at the 10% only, Non-Farm Payrolls provide the largest reaction. Averaged across the 38 jumps caused by this announcement, a standard deviation suprise in this indicator causes an increase in the size of intraday jumps of 0.349 in absolute terms. Compared to the sample average five-minute return of zero and average absolute jump size of 0.252, excluding news related jumps, this represents an economically significant increase. As α of the jump detection procedure is lowered, Consumer Confidence, GDP Advance, ISM Index, Non-Farm Payrolls, Retail Sales, Trade Balance and Unemployment Rate all remain important and significant announcements with larger coefficient estimates in absolute terms and larger R^2 in the majority of cases. Panel (B) shows the same results using standardised returns. Given the restrictive nature of this standardisation prior to jump detection at a conservative significance level, it is perhaps not surprising that there are very few indicators with sufficient observations to be included. Non-Farm Payrolls is highlighted as the only important release, showing higher coefficient estimates and R^2 than in Panel (A). Interestingly, the Unemployment Rate is not significant, even though it is released at the same time as Non-Farm Payrolls as part of the Employment Report, showing that the informational content of these separate announcements is important.

Table 4.5.4.2 shows the results for GBP-USD futures. Consistent with the results for EUR-USD, Consumer Confidence, GDP Advance, ISM Index, Non-Farm Payrolls, Retail Sales and Trade Balance are significant indicators, along with Construction Spending. This is a very different list to those important indicators for regressions using dummy variables. Again, coefficients for these significant announcements are large and their regressions show R^2 values above 0.5 and ranging up to 0.856. Retail Sales displays a particularly high coefficient value showing that a unit standard deviation positive (negative) surprise corresponds to an appreciation (depreciation) of USD relative to GBP by a jump of 1.532, which is an enormous five-minute price move. This is vast compared to average five-minute returns of approximately zero and average absolute intraday jumps for non-announcment intervals of 0.186. The corresponding R^2 is a striking 0.808 showing that the vast majority of these 8 intraday jumps are explained by news. The coefficient for Non-Farm Payrolls of -0.392 is similar to that of EUR-USD and this is clearly the announcement causing the most jumps for GBP-USD with 27 jumps generating a high R^2 of 0.702 for this regression. Consumer Confidence, GDP Advance, Non-Farm Payrolls and Trade Balance remain significant indicators for the more stringent α=0.0001 version of the test and retain remarkably similar values for γ_δ and R^2, but the dramatic influence of Retail Sales does not produce at least 5 jumps in this case.

Standardising returns also removes many jumps from the sample leaving Non-Farm Payrolls as the only significant announcement at the 5% level or lower.

To complete the analysis of the foreign exchange futures, Table 4.5.4.3 shows the results for the JPY-USD futures market. Again, Non-Farm Payrolls, Retail Sales and Trade Balance are the significant announcements showing large, statistically and economically significant coefficient values and striking R^2 measures. Retail Sales announcements do not generate enough jumps to be included for lower α, but Initial Claims is added to the list and with a very high R^2. Standardised returns jumps show Non-Farm Payrolls and the Unemployment Rate as significant at the 10% level only for α=0.001, whilst FOMC announcements make their only significant appearance in all of the foreign exchange futures markets with unexpected hikes in interest rates causing significant USD appreciation relative to JPY.

Table 4.5.4.4 shows the results for S&P 500 E-Mini futures and there is a distinct lack of significant announcements compared to the foreign exchange futures discussed above. Construction Spending and Consumer Confidence both exhibit positive estimates of γ_δ that are significantly different from zero showing that higher than expected announcements cause large, positive increases in the size of intraday jumps. The R^2 values for these two indicators are also remarkably large. FOMC interest rate announcements are the only other source of significant announcements. A large negative coefficient for FOMC implies that larger than expected hikes in the Fed Funds rate causes a sharp negative jump in this market. Whilst this lack of significance of indicators, particularly GDP Advance and Non-Farm Payrolls, is surprising compared to foreign exchange and interest rate futures, and the results of the previous section using simple dummy variables, this result confirms the recent findings of Andersen, Bollerslev, Diebold and Vega (2007) for earlier samples of S&P 500, FTSE and DJ Euro Stoxx 50 futures markets. Lowering the level of α for the jump test and standardising returns to annihilate the intraday volatility pattern provides only FOMC decisions as significant, with the data in Table 4.5.4.4 identical for this indicator throughout all four versions of the test.

The lack of significant announcements is also a feature of FTSE 100 futures in Table 4.5.4.5, with only Consumer Confidence showing statistical significance at the 5% level or lower for raw returns and under both levels of α. This is perhaps less surprising given that many indicators in Table 4.5.2.5 show fewer than 5 instances of announcements corresponding to jumps for α=0.001 and 0.0001. As with the S&P

500 E-Mini market above, the lack of statistical significance of GDP Advance and Non-Farm Payrolls presents more of a surprise given their importance when using simple dummy variables and across other markets.

DJ Euro Stoxx 50 futures, in contrast, reveal significant news reactions for Consumer Confidence, GDP Advance, Initial Claims, ISM Index and Productivity Preliminary, most with extremely high values of R^2, as shown in Table 4.5.4.6. Coefficient values suggest that unexpected positive news regarding the US macroeconomy causes positive jumps in DJ Euro Stoxx 50 futures returns. Consumer Confidence, GDP Advance and ISM Index remain statistically significant for the more stringent level of α with superior measures of R^2, and these are joined by Chicago PMI. Most of these announcements match those that are significant in Table 4.5.2.6 for simple dummy variables, but the exclusion of data from the Employment Report remains surprising given its documented importance.

To complete the analysis, Tables 4.5.4.7 to 4.5.4.9 show the results for the interest rate futures markets, beginning with the US 10-Year T-Bond futures. In confirmation of the findings of the previous section, this is the most responsive market to US macroeconomic news in terms of both the number of jumps caused by news and the number and range of indicators showing statistically significant reactions. The important indicators are Capacity Utilization, Chicago PMI, Consumer Confidence, Employment Cost Index, Factory Orders, GDP Advance, Industrial Production, Initial Claims, ISM Index, New Home Sales, Non-Farm Payrolls, PPI, Retail Sales and the Unemployment Rate, showing both large coefficient estimates in absolute terms and large R^2 values. The signs of coefficients show that positive US news innovations cause reductions in the price of the 10-Year Treasury future, consistent with a rise in its yield. The largest reactions are found for Retail Sales and Non-Farm Payrolls, for which one standard deviation positive surprises generate average negative jumps of 0.606 and 0.361 respectively. For Retail Sales, this is almost three times the average absolute intraday jump excluding jumps coinciding with this indicator, and almost twice the same average for Non-Farm Payrolls, showing the dramatic economic significance of these reactions. High R^2 values emphasise the economic significance of these relationships between jumps and news and, although they are lower for this market than others considered in this chapter due to the vastly higher number of observations in each regression, they remain larger than those reported in Chapter 3 and the extant literature, which consider all returns rather than jumps only. Lowering the level of α for the jump test retains all significant announcements, with most showing increases in R^2. Despite the restrictive nature of standardising returns on the jump test, Capacity Utilization, Industrial Production and Non-Farm Payrolls remain significant in Panel (B), the latter showing dramatically larger values of γ_δ and R^2, which are retained for the lower level of α for the test, demonstrating the influence of this indicator.

Table 4.5.4.8 shows the results for the UK Gilt futures market. The table shows many more significant announcements than Table 4.5.2.8 using dummy variables and these include Chicago PMI, Construction Spending, Consumer Confidence, CPI, GDP Advance, ISM Index, Michigan Sentiment Preliminary, Non-Farm Payrolls, Retail Sales and Unemployment Rate, many of which have been identified as important in other markets. Coefficient estimates show that surprising positive news about the US economy drives UK Gilt futures lower and yields higher. Consistent with the US 10-Year T-Bond futures market, Retail Sales and Non-Farm Payrolls show the strongest reactions with one standard deviation positive surprises causing average reductions in the UK Gilt futures returns of 0.449 and 0.191 respectively. Lowering the level of α for the test retains many of these indicators as significant, often with larger coefficient estimates in absolute terms and larger R^2, whilst the standardisation of returns eliminates all announcements except the Employment Report. Somewhat surprising in this table is the inclusion of Bank of England announcements causing 10 jumps, but not as a significant relationship between intraday jumps and standardised news, suggesting that this indicator provides pure announcement effects only.[32]

The final market to consider is that of the Euro Bund shown in Table 4.5.4.9. The data confirms the interest rate futures markets as most responsive to news with Chicago PMI, Consumer Confidence, GDP Advance, ISM Index, Michigan Sentiment Preliminary, Non-Farm Payrolls, Retail Sales and the Unemployment Rate all showing statistically significant influences on Euro Bund jumps. Positive US macroeconomic news causes negative jumps, and vice versa with the most dramatic effects on jumps shown for Non-Farm Payrolls and GDP Advance. The R^2 measures are striking throughout, showing that large proportions of the jumps are explained by

[32] Alternatively, this lack of significance may result from the use of interst rate expectations being derived from short term interest rate futures prices rather than survey data, and this may be an important avenue for future research.

the standardised news variables. To confirm the economic significance of these reactions, a 'typical' one standard deviation surprise in Non-Farm Payrolls causes an average jump in Euro Bund futures of 0.179 in absolute terms, which dwarfs the sample average five-minute return of zero and is larger than the average absolute intraday jump of 0.141, excluding jumps relating to Non-Farm Payroll announcements.

To conclude this section, these results have confirmed the important influence of US macroeconomic news announcements, beyond pure announcement effects, to realte jumps with the information surprise of data releases. Many indicators, particularly for foreign exchange and interest rate futures, show statistically and economically significant responses in intraday jumps to news surprises. The R^2 values are striking in all markets, showing that large proportions of the variation in jumps are explained by information surprises. It is interesting that unexpected strengthening of the US macroeconomy causes jumps which appreciate the dollar, and also cause positive jumps in US, UK and European stock markets and negative jumps in world bond prices. The transmission mechanism of such news effects and possible spillovers across markets is an interesting area that could be investigated in future work. Another interesting enquiry would be to investigate the lack of significant news for equity markets. This contradicts the findings of the previous section that uses simple dummy variables and may be explained by the aggregation of asymmetric effects of some news indicators across business cycle conditions. The separation of such effects may enlighten more complex dynamics of the relationship between equity retuns and macroeconomic news as suggested by Andersen, Bollerslev, Diebold and Vega (2007).

4.5.5 Sequential Intraday Jumps and Standardised News

To complete the analysis, this final section of results repeats the regressions of intraday jumps on standardised indicators for sequentially identified intraday jumps, allowing a comparison of the relationships between news and jumps across jump identification techniques. To differentiate the notation from the previous section, the regression takes the form:

$$\widetilde{\kappa}_k = \varpi_\delta + \gamma_\delta S_{\delta,k} + \xi_{\delta,k}, \tag{4.44}$$

such that $\widetilde{\kappa}_k$ identifies the sequential intraday jumps, according to the method of Andersen, Bollerslev, Frederikesn and Nielsen (2006), with separate estimation performed for each macroeconomic indicator, δ, that exhibits at least five occurrences of jumps coinciding with the relevant news release. Regressions contain only those intraday jump intervals that contain news announcements and are performed for alternative $Z_{1,t}$ and $U_{1,t}$ versions of the sequential intraday jumps test for significance levels of α=0.001 and 0.0001. The results, which include estimated values of γ_δ and the regression R^2, are displayed in Tables 4.5.5.1 to 4.5.5.9 for each futures market.

In general, Tables 4.5.5.1 to 4.5.5.9 show strong consistency between the $Z_{1,t}$ and $U_{1,t}$ versions of the test. For the vast majority of indicators, both versions exhibit similar numbers of occurrences of jumps and news, coefficient estimates and R^2 measures, consistent with the similar comparison of Tables 4.5.3.1 to 4.5.3.9. The numbers of sequential intraday jumps caused by news are generally lower than the raw returns intraday jumps of the previous section, but higher than the standardised returns intraday jumps. These fewer intraday jumps often generate larger coefficient estimates in absolute terms and larger R^2 measures, showing stronger relationships between these jumps and news surprises. The sequential method, therefore, detects fewer jumps than the raw returns intraday method, but retains the larger jumps, some of which are very strongly related to unexpected news. However, with relatively few observations in regressions for some indicators, small changes in the jumps detected can display sizeable changes in the results and this is seen occasionally when comparing the different versions of the sequential jump test in Panels (A) and (B) in the tables.

In each of the markets considered, coefficient estimates show statistical and economic significance of the impact of news on intraday jumps and also show extremely large values of R^2 showing that the news on economic fundamentals explains large proportions of the variation of intraday jump sizes. Consistent with the findings of the previous section, intraday jumps in equity index futures markets show very little reaction to news, which is in direct contrast to the dramatic effects of news announcement dummies investigated in sections 4.5.2 and 4.5.3, and may suggest more complex, asymmetric relationships that are not identified in this study.

Table 4.5.5.1. Sequential Intraday Jumps and Standardised News for EUR-USD Futures.

A	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
		No. Jumps: 239			No. Jumps: 126	
Consumer Confidence	7	**-0.258****	0.958			
Initial Claims	13	0.088	0.082	9	**0.341+**	0.402
Non-Farm Payrolls	22	**-0.432****	0.640	17	**-0.524****	0.711
PPI	5	0.457	0.474			
Trade Balance	6	**-0.199***	0.750	6	**-0.199***	0.750
Unemployment Rate	22	0.131	0.071	17	0.121	0.050
FOMC	6	-0.056	0.002			
(B) Sequential Intraday Jumps using $U_{1,t}$						
		No. Jumps: 281			No. Jumps: 177	
Business Inventories	5	0.187	0.217			
Consumer Confidence	8	**-0.257****	0.903	5	-0.166	0.314
Initial Claims	15	0.082	0.100	11	0.021	0.004
NY Empire State Index	5	**-0.331***	0.771			
Non-Farm Payrolls	23	**-0.342****	0.500	20	**-0.337****	0.476
PPI	5	0.457	0.474	5	0.457	0.474
Trade Balance	6	**-0.199***	0.750	6	**-0.199***	0.750
Unemployment Rate	23	**0.153+**	0.099	20	0.138	0.078
FOMC	6	-0.009	0.000			

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in EUR-USD futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_{\delta,k}, \widetilde{K}_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.2. Sequential Intraday Jumps and Standardised News for GBP-USD Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 481			No. Jumps: 286		
Consumer Confidence	5	**-0.199****	0.919			
Initial Claims	7	0.055	0.098	5	0.068	0.170
Non-Farm Payrolls	14	**-0.375****	0.830	12	**-0.377****	0.819
Trade Balance	6	**-0.159***	0.693	5	**-0.213+**	0.735
Unemployment Rate	14	0.053	0.022	12	0.010	0.001
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 543			No. Jumps: 380		
Consumer Confidence	5	**-0.199****	0.919			
Initial Claims	9	0.042	0.099	8	0.056	0.094
Non-Farm Payrolls	17	**-0.381****	0.793	13	**-0.374****	0.814
Trade Balance	7	**-0.159***	0.700	6	**-0.159***	0.728
Unemployment Rate	17	0.087	0.066	13	0.004	0.000

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in GBP-USD futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_{\delta,k}, \widetilde{K}_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that $\gamma_\delta=0$. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.3. Sequential Intraday Jumps and Standardised News for JPY-USD Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 253			No. Jumps: 121		
Non-Farm Payrolls	12	-0.214	0.257	11	-0.212	0.256
Trade Balance	5	**-0.145+**	0.569			
Unemployment Rate	12	0.041	0.009	11	-0.006	0.000
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 328			No. Jumps: 196		
Non-Farm Payrolls	14	-0.210	0.253	12	**-0.364****	0.472
Trade Balance	5	**-0.145+**	0.569			
Unemployment Rate	14	0.038	0.008	12	0.037	0.007

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in JPY-USD futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_{\delta,k}, \widetilde{K}_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.4. Sequential Intraday Jumps and Standardised News for S&P 500 E-Mini Futures.

α	0.001			0.0001		
	N($S_{\delta,k}$, $\widetilde{K}_k$)	γ_δ	R^2	N($S_{\delta,k}$, $\widetilde{K}_k$)	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 129			No. Jumps: 57		
Business Inventories	5	0.070	0.076			
CPI	9	-0.113	0.070	6	-0.209	0.211
Non-Farm Payrolls	15	0.224	0.070	9	0.038	0.001
Unemployment Rate	15	-0.164	0.043	9	-0.098	0.014
FOMC	5	-0.350	0.062	5	-0.350	0.062
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 171			No. Jumps: 88		
Business Inventories	6	0.071	0.076			
CPI	11	-0.039	0.016	7	-0.181	0.185
Non-Farm Payrolls	17	0.251	0.079	12	0.051	0.003
Unemployment Rate	17	-0.245	0.101	12	-0.102	0.018

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in S&P 500 E-Mini futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). N($S_{\delta,k}$, $\widetilde{K}_k$) represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.5. Sequential Intraday Jumps and Standardised News for FTSE 100 Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 193			No. Jumps: 97		
Initial Claims	5	**-1.021***	0.521			
Non-Farm Payrolls	5	0.278	0.020			
Unemployment Rate	5	-0.317	0.083			
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 226			No. Jumps: 128		
Initial Claims	5	**-1.021***	0.521			
Non-Farm Payrolls	7	0.100	0.014			
Unemployment Rate	7	-0.256	0.072			

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in FTSE 100 futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_{\delta,k}, \widetilde{K}_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.6. Sequential Intraday Jumps and Standardised News for DJ Euro Stoxx 50 Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 310			No. Jumps: 157		
Business Inventories	5	-0.924	0.176			
Consumer Confidence	5	**0.370***	0.715			
CPI	5	-0.278	0.233	5	-0.278	0.233
GDP Advance	5	**1.011***	0.741			
Initial Claims	8	-0.200	0.038	6	-0.316	0.105
ISM Manufacturing	5	**0.433****	0.781			
Non-Farm Payrolls	16	0.261	0.044	13	0.247	0.032
PPI	5	-0.378	0.136			
Retail Sales	6	2.984	0.323			
Unemployment Rate	16	-0.124	0.021	13	-0.157	0.033
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 323			No. Jumps: 196		
Business Inventories	6	-0.652	0.101			
Consumer Confidence	5	**0.370***	0.715			
CPI	6	-0.275	0.231			
GDP Advance	5	**1.011***	0.741			
Initial Claims	9	-0.295	0.124	6	-0.316	0.105
ISM Manufacturing	6	**0.405****	0.671			
Non-Farm Payrolls	16	0.275	0.047	15	0.283	0.047
Retail Sales	5	2.535	0.252			
Unemployment Rate	16	-0.113	0.020	15	-0.126	0.022

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in DJ Euro Stoxx 50 futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_{\delta,k}, \widetilde{K}_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.7. Sequential Intraday Jumps and Standardised News for US 10-Year T-Bond Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 517			No. Jumps: 312		
Business Inventories	8	0.087	0.054	5	0.027	0.003
Chicago PMI	7	**-0.180***	0.708	5	**-0.278***	0.799
Construction Spending	14	**0.134****	0.268	6	**0.306+**	0.283
Consumer Confidence	7	**-0.148****	0.980			
CPI	13	0.044	0.033	12	0.038	0.024
Employment Cost Index	8	**-0.288***	0.388	6	**-0.261+**	0.397
Factory Orders	5	**-0.139****	0.884			
GDP Advance	8	-0.219	0.358	5	-0.171	0.303
Housing Starts	6	0.019	0.011	5	-0.043	0.033
Initial Claims	26	0.054	0.084	17	**0.102+**	0.125
ISM Manufacturing	15	**-0.137****	0.569	6	**-0.117***	0.706
New Home Sales	7	**-0.101***	0.608	5	**-0.099***	0.577
NY Empire State Index	5	-0.072	0.036			
Non-Farm Payrolls	29	**-0.517****	0.645	21	**-0.547****	0.705
PPI	9	-0.076	0.178			
Retail Sales	18	**-1.175***	0.291	13	**-1.559***	0.404
Unemployment Rate	29	0.138	0.055	21	0.010	0.000
FOMC	9	-0.167	0.249	9	-0.167	0.249
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 528			No. Jumps: 364		
Business Inventories	10	0.097	0.069	6	0.060	0.020
Chicago PMI	7	**-0.180***	0.708	6	**-0.267****	0.806
Construction Spending	12	0.161	0.113	10	0.099	0.049
Consumer Confidence	8	**-0.108***	0.605	6	**-0.148****	0.982
CPI	17	0.003	0.000	15	0.020	0.007
Employment Cost Index	7	**-0.277***	0.389	6	**-0.261+**	0.397
Factory Orders	6	**-0.118***	0.621	6	**-0.118***	0.621
GDP Advance	7	-0.205	0.340	6	-0.220	0.465
Housing Starts	6	0.019	0.011	6	0.019	0.011
Initial Claims	29	**0.058+**	0.096	21	0.045	0.044
ISM Manufacturing	12	**-0.121****	0.676	10	**-0.111****	0.638
New Home Sales	7	**-0.085***	0.407	5	**-0.099***	0.577
NY Empire State Index	6	-0.071	0.049			
Non-Farm Payrolls	26	**-0.495****	0.631	19	**-0.500****	0.671
PPI	11	-0.081	0.140	7	-0.091	0.063
Retail Sales	20	**-1.280***	0.362	16	**-1.573***	0.431
Unemployment Rate	26	0.070	0.013	19	-0.105	0.014
FOMC	8	-0.158	0.214	5	-0.218	0.448

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in US 10-Year T-Bond futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_{\delta,k}, \widetilde{K}_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.8. Sequential Intraday Jumps and Standardised News for UK Gilt Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{\kappa}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{\kappa}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 560			No. Jumps: 320		
Consumer Confidence	6	**-0.119****	0.823			
CPI	6	-0.085	0.225			
Employment Cost Index	5	0.040	0.026			
GDP Advance	6	**-0.221***	0.826			
Initial Claims	8	0.083	0.108			
Non-Farm Payrolls	25	**-0.194****	0.377	21	**-0.261****	0.517
PPI	6	0.059	0.104	5	0.046	0.099
Retail Sales	7	**-0.312****	0.676	5	**-0.759****	0.707
Unemployment Rate	25	**0.126****	0.175	21	**0.130****	0.157
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 589			No. Jumps: 373		
Consumer Confidence	6	**-0.119****	0.823	5	**-0.117***	0.784
Employment Cost Index	5	0.040	0.026	5	0.040	0.026
GDP Advance	6	**-0.221***	0.826	5	**-0.262***	0.829
Initial Claims	8	0.060	0.064	6	0.065	0.067
Non-Farm Payrolls	21	**-0.221****	0.498	16	**-0.282****	0.691
PPI	6	0.059	0.104			
Retail Sales	6	**-0.755****	0.717			
Unemployment Rate	21	**0.123****	0.171	16	**0.120***	0.155

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in UK Gilt futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_k, \kappa_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that γ_δ=0. Each regression uses only those jumps which coincide with macroeconomic announcements.

Table 4.5.5.9. Sequential Intraday Jumps and Standardised News for Euro Bund Futures.

α	0.001			0.0001		
	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2	$N(S_{\delta,k}, \widetilde{K}_k)$	γ_δ	R^2
(A) Sequential Intraday Jumps using $Z_{1,t}$						
	No. Jumps: 393			No. Jumps: 232		
Chicago PMI	5	**-0.093****	0.951			
Construction Spending	6	0.044	0.093			
Consumer Confidence	6	**-0.078****	0.958			
CPI	5	**-0.100***	0.667			
Employment Cost Index	9	-0.077	0.079	7	-0.113	0.201
GDP Advance	10	**-0.198****	0.740	8	**-0.183****	0.687
Initial Claims	17	**0.064+**	0.074	12	0.029	0.014
ISM Manufacturing	9	**-0.097****	0.734	5	**-0.134****	0.980
Mich Sentiment Prel	6	-0.079	0.566	5	-0.081	0.580
Non-Farm Payrolls	24	**-0.256****	0.507	22	**-0.286****	0.551
PPI	7	-0.043	0.063	6	-0.041	0.075
Retail Sales	10	**-0.811****	0.548	6	**-0.997***	0.637
Unemployment Rate	24	**0.116****	0.154	22	**0.122****	0.170
(B) Sequential Intraday Jumps using $U_{1,t}$						
	No. Jumps: 393			No. Jumps: 248		
Chicago PMI	5	**-0.093****	0.951	5	**-0.093****	0.951
Consumer Confidence	6	**-0.092****	0.873			
CPI	5	**-0.149****	0.658			
Employment Cost Index	8	-0.095	0.153	7	-0.113	0.201
GDP Advance	8	**-0.183****	0.718	7	**-0.181***	0.692
Initial Claims	15	0.005	0.001	13	0.039	0.028
ISM Manufacturing	7	**-0.099****	0.846			
Mich Sentiment Prel	5	-0.081	0.580			
Non-Farm Payrolls	23	**-0.263****	0.485	19	**-0.306****	0.537
PPI	7	-0.043	0.063	6	-0.041	0.075
Retail Sales	10	**-1.006***	0.550	5	**-0.845***	0.614
Unemployment Rate	23	**0.120****	0.174	19	0.131	0.206

Notes: The table shows data relating to the impact of US macroeconomic announcements on intraday jumps detected in Euro Bund futures returns. Intraday jumps are detected according to the sequential method of equations (4.37) and (4.38) across a range of significance levels (α). $N(S_{\delta,k}, \widetilde{K}_k)$ represents the number of intraday jumps coinciding with macroeconomic announcements. Only those indicators with at least five coincidences of news and jumps are displayed. γ_δ reports the estimated coefficient from equation (4.44) with **, * and + denoting statistical significance at the 1, 5 and 10% levels respectively for a two-tailed test of the null that $\gamma_\delta=0$. Each regression uses only those jumps which coincide with macroeconomic announcements.

Interest rate futures markets, however, and the US 10-Year T-Bond market in particular, show greater responsiveness to the information content of economic news showing more indicators with significant coefficients based on more frequent coincidences of jumps and news. As identified above, the important releases are Consumer Confidence, GDP Advance, Non-Farm Payrolls, Retail Sales and Trade Balance, with occasional differences between markets that are discussed in the following summary of the results.

Table 4.5.5.1 shows the results for EUR-USD futures and confirms the similarity in results between $Z_{1,t}$ and $U_{1,t}$ according to the magnitude of coefficient estimates for the statistically significance indicators and the size of the regression R^2. Consumer Confidence, Non-Farm Payrolls and Trade Balance are the most important indicators, the latter two also being significant for intraday jumps detected according to α=0.0001. In comparison with the results of the previous section, the number of coincidences of jumps and news are lower than for raw returns causing larger coefficients in absolute terms in many cases and larger values of R^2. The opposite is seen when comparing the results for sequential intraday jumps with those of standardised return intraday jumps, suggesting that the sequential method offers a 'compromise' between the raw and standardised return intraday jump detection techniques. The more restrictive sequential test generates fewer jumps overall and fewer jumps coinciding with news announcements than the raw returns intraday technique, explaining the omission of GDP Advance, ISM Index and New Home Sales that are found to be significant in the previous section. To emphasise the economic significance of the indicators, one standard deviation positive surprises cause appreciation of USD against EUR of 0.258, 0.432 and 0.199 on average for Consumer Confidence, Non-Farm Payrolls and Trade Balance, respectively (all for $Z_{1,t}$). These are enormous average returns for the five-minute intervals immediately following these announcements, compared to average five-minute returns of zero over the sample, and are also large compared to average absolute intraday jumps of 0.269, 0.243 and 0.266 for the samples of intraday jumps not including the announcement related intervals.

The GBP-USD futures market is represented in Table 4.5.5.2 and shows almost identical results between $Z_{1,t}$ and $U_{1,t}$ versions of intraday jumps. Consistent with EUR-USD, Consumer Confidence, Non-Farm Payrolls and Trade Balance are the important indicators showing average instantaneous five-minute jumps of 0.199, 0.375 and 0.159 in response to unexpected news that appreciate USD against GBP if the news reflects unexpected strength of the US economy. These are statistically significant reactions, the news surprises explain proportions of 0.919, 0.830 and 0.693 of these jumps, and compare to average absolute sequential intraday jumps of 0.162, 0.154 and 0.160 showing at least a doubling of the size of jumps in response to a single standard deviation news surprise, confirming their economic significance. These indicators are the same ones identified by announcement dummy variables in section 4.5.3, and Non-Farm Payrolls is retained for a lower level of α confirming it as the most important release of all.

In contrast to EUR-USD and GBP-USD, JPY-USD futures do not show much impact of standardised news on sequential intraday jumps. Whilst the results in Table 4.5.5.3 confirm the consistency between the two versions of the sequential test, they also show that very few economic indicators cause five or more jumps for this market. Indeed, only the Employment Report and Trade Balance cause sufficient jumps to be included and only Non-Farm Payrolls shows statistical significance, but for α=0.0001 and the $U_{1,t}$ version only. These findings confirm the earlier results of section 4.5.3, which show that many isolated announcements cause intraday jumps in JPY-USD futures, but very few indicators exhibit systematic effects on this instrument.

Turning to the equity index futures markets, Table 4.5.5.4 shows the results for the S&P 500 E-Mini market. In stark contrast to the results of section 4.5.3 using simple news announcement dummies, which show announcements to cause dramatic effects on intraday jumps, there are no significant relationships between jumps and news surprises. This is irrespective of the version or significance level of the intraday jump tests employed and corroborates the corresponding results for raw and standardised returns intraday jumps of section 4.5.4, with the exception of FOMC. The number of jumps coinciding with individual economic indicators is smaller than for raw returns intraday jumps and similar to those for standardised returns intraday jumps. This restrictive nature of the sequential intraday jump test may explain the lack of significant relationships. However, since it is expected that these more restricitive tests would retain the larger intraday returns as jumps, there may be other asymmetric dynamics present in the S&P 500 E-Mini futures market that are unidentified in these simple regressions.

A similar lack of significant results is shown by FTSE 100 futures in Table 4.5.5.5. With very few indicators showing five or more intraday jumps for α=0.001 and none for α=0.0001, this is perhaps not surprising. Only Initial Claims shows a significant relationship and the negative coefficient suggests that positive US employment news generates positive and significant jumps in FTSE 100 futures returns. In comparison to the intraday jumps of section 4.5.4, the sequential intraday jump method finds fewer instances of jumps caused by news announcements than for both raw and standardised intraday returns, and this explains the omission of Consumer Confidence and GDP Advance as significant indicators. Consistent with the analysis of simple announcement dummy variables, these results confirm that only a few isolated news events cause intraday jumps in FTSE 100 futures and there are very limited systematic relationships between jumps and news. Of course, it is possible that UK news may show more of an impact than the US news implemented here, however, preliminary investigation, as discussed in sections 4.5.2 and 4.5.3, reveal that this is unlikely, but is left for future work.

DJ Euro Stoxx 50 futures, whose results are displayed in Table 4.5.5.6, show a more influential role for macroeconomic news surprises in explaining the size of sequential intraday jumps. GDP Advance causes a massive jump of 1.011 in the interval following a standard deviation news surprise, with positive news on the US economy driving this European stock index upwards. This reaction compares with sample average five-minute returns of zero and average absolute intraday jumps of 0.438, when excluding these GDP Advance announcement intervals. This dramatic reaction is therefore statistically and economically significant and the R^2 value of 0.741 confirms its importance in explaining the variation in the sizes of these intraday jumps. GDP Advance is important for both $Z_{1,t}$ and $U_{1,t}$ versions of the test and Consumer Confidence and ISM Index are also important under the $Z_{1,t}$ specification with large, significant coefficients of 0.370 and 0.433 and also high R^2 values of 0.715 and 0.781 respectively. The identification of these indicators is entirely consistent with the foreign exchange futures markets of Tables 4.5.5.1 to 4.5.5.3, but is at odds with the US and UK equity index futures markets. Consistent across the three stock index futures, however, is the absence of Non-Farm Payrolls as a significant indicator (at the 5% level or lower), which is contrary to the other asset classes. Reducing the significance level of the sequential intraday jump test to

α=0.0001 removes many intraday jumps and leaves no economic indicators showing significant relationships with the remaining jumps.

Turning attention to the interest rate futures markets, Tables 4.5.5.7 to 4.5.5.9 confirm the results of section 4.5.4 that these markets respond most often to US macroeconomic news. The US 10-Year T-Bond futures market shows the highest number of intraday jumps caused by news and also the most significant individual announcements of all markets, as shown by Table 4.5.5.7. The number of intraday jumps in each individual regression is slightly different for the $U_{I,t}$ version of the test in Panel (B) and coefficient estimates and R^2 values tend to be slightly different in absolute terms but, despite these minor discrepancies, there is tremendous consistency between the $Z_{I,t}$ and $U_{I,t}$ detection methods. Coefficient estimates are large and negative, implying that news conveying unexpected strength of the US economy drives bond prices lower and thus yields higher. R^2 values are striking also, extending to 0.884 and 0.980 in extreme cases. Coefficients are significant for the more conservative α=0.0001 version of the test, confirming the importance of these relationships. The individual announcements identified in both Panel (A) and (B) are Chicago PMI, Consumer Confidence, Employment Cost Index, Factory Orders, ISM Index, Non-Farm Payrolls and Retail Sales, with the surprising omission of GDP Advance and FOMC decisions. The largest reactions occur for Retail Sales and Non-Farm Payrolls, showing five-minute jumps of 1.175 and 0.517 in response to one standard deviation surprises. These compare to average five-minute returns of zero over the entire sample and to absolute average sequential intraday jumps of 0.160 and 0.141 for jumps that do not contain these announcements, emphasising the incredible economc significance of these instantaneous reactions to news. Coefficients and R^2 figures are much larger than those reported by Andersen, Bollerslev, Diebold and Vega (2007) for the US 30-Year T-Bond futures market demonstrating the dramatic influence of news in causing intraday price jumps.

The UK Gilt futures market is represented in Table 4.5.5.8, which, in confirmation of other markets, shows Consumer Confidence, GDP Advance, Non-Farm Payrolls and Retail Sales as significant indicators. In contrast to most other markets, the Unemployment Rate released as part of the Employment Report is also significant for this market. The table confirms the consistency between $Z_{I,t}$ and $U_{I,t}$ versions of the test with results very similar between Panels (A) and (B), although a difference of one observation for Retail Sales causes a dramatic change in its coefficient between the panels. R^2 measures are again large, coefficients show economic significance when compared to average returns and average absolute jumps, and many indicators remain significant for α=0.0001. Compared to Table 4.5.4.8, the sequential method detects fewer intraday jumps coinciding with news than raw returns intraday jumps, resulting in the larger jumps retained by the sequential method displaying larger coefficients in absolute terms. Similar to the US 10-Year T-Bond futures market, news of a stronger US economy causes negative jumps in UK Gilt prices, and therefore positive jumps in yields.

Finally, Table 4.5.5.9 shows the results for the Euro Bund futures market. Figures are very consistent between Panels (A) and (B) showing only minor differences between the $Z_{1,t}$ and $U_{1,t}$ versions of the test. The number of jumps coinciding with news is slightly lower for $U_{1,t}$, but coefficient estimates and R^2 values remain large. Comparing these results with those in Table 4.5.4.9, the sequential intraday jumps show many fewer instances of news causing jumps, but the larger jumps that are retained are associated with larger coefficient estimates in absolute terms and larger proportions of the jumps explained by news surprises. Consistent with the foreign exchange and other interest rate futures markets, the important individual economic indicators are Chicago PMI, Consumer Confidence, GDP Advance, ISM Index, Non-Farm Payrolls and Retail Sales, whilst CPI and Unemployment Rate are also important for this market, and many of these variables remain important in the more stringent α=0.0001 version of the tests. The coefficient signs suggest that positive news causes downward jumps in Euro Bund prices, corresponding to positive jumps in yields. The economic significance of these relationships is confirmed by comparing the coefficient sizes for Non-Farm Payrolls and Retail Sales of 0.256 and 0.811, with average absolute non-announcement jumps of 0.125 and 0.135 respectively. The jumps in response to a typical one standard deviation surprise in Non-Farm Payrolls is therefore more than double the average absolute intraday jump and more than four times the same average for Retail Sales. There is stong evidence, therefore, that these information surprises are responsible for causing dramatic, statistically and economically significant instantaneous jumps in asset prices.

To conclude this section, the results shown in Tables 4.5.5.1 to 4.5.5.9 corroborate the importance of economic news in causing jumps in financial markets. Although macroeconomic news announcements do not explain all intraday jumps, those that they do cause are large. The estimated coefficient signs reveal that global futures markets are linked to economic fundamentals. More specifically, the magnitude of the coefficients defining these relationships are surprisingly large and economically significant and the R^2 values measuring the extent to which informational surprises explain the variation in intraday jump sizes caused by the news shocks are striking. Across the asset classes, interest rate futures show the most sensitivity to macroeconomic news, followed by foreign exchange futures, with stock index futures showing no systematic relationship between the information content of news releases and the jumps that they cause.

The most important individual announcements are Consumer Confidence, GDP Advance, ISM Index, Non-Farm Payrolls and Retail Sales, while Chicago PMI, Employment Cost Index and New Home Sales also important for US 10-Year T-bond futures, and the Trade Balance is also important for the foreign exchange futures. These announcements correspond to those identified as important in the extant literature, however, the magnitude of coefficients and R^2 measures are much larger for the intraday jumps in sections 4.5.4 and 4.5.5 in this chapter than for the returns used in Chapter 3 and other studies. This provides further evidence that unexpected macroeconomic news announcements cause intraday jumps with those jumps very strongly correlated with the information contained in the data release. Non-Farm Payrolls maintains its standing as the most important of all macroeconomic announcements, causing more jumps and larger coefficients than any other announcement across all markets when investigated in terms of both simple announcement dummies and standardised news variables. Somewhat surprisingly, equity index markets show no statistical relationship between unexpected news on this indicator and intraday jumps, however, a strong influence is detected in these markets by announcement dummies. This suggests, perhaps, that conflicting, asymmetric effects are present that cannot be separated in the simple regressions of sections 4.5.4 and 4.5.5, and it will be interesting to research this issue further.

Empirically, there is strong consistency between the $Z_{I,t}$ and $U_{I,t}$ versions of the test, which confirms the findings of the previous sections, and the sequential method seems a more stringent jump detection method than the raw returns intraday jump technique, finding fewer jumps caused by news, but these jumps provide higher coefficients and R^2 measures. Irrespective of the nuances of these intraday jump measurement techniques, the results presented in section 4.5 reveal overwhelming evidence of strong links between news on economic fundamentals and futures prices as manifested through instantaneous jumps.

4.6 CONCLUSION

The distributional properties of asset returns and the dynamics of return volatility have remained two very popular areas of research in financial economics over the last decades, making important contributions to our understanding of the risk-return tradeoff so crucial for asset pricing, portfolio allocation, risk management techniques and derivative pricing. Arguably, the most important developments along these lines have been based on continuous-time theory and methods, and the latest research suggests the incorporation of discontinuities, or jumps, and stochastic volatility is essential in accommodating the empirical regularities of extreme returns causing fat-tailed distributions and temporal dependence, clustering, persistence and feedback effects in volatility. In light of these findings, this study implements a continuous-time jump-diffusion log-price model as the foundation for an investigation into financial market jumps.

In parallel with the development of the parametric continuous-time literature, powerful non-parametric techniques have been advanced recently that rely solely on the availability of high frequency asset price data, which has become easily accessible over the last decade. The resulting literature concerning the measurement and forecasting of (realised) volatility has grown to become a substantive contribution of financial economic research. Combining these non-parametric techniques with the continuous-time framework, the most recent research provides the ability to separate continuous and discontinuous components of quadratic variation, which have been used to improve the forecasting of daily volatility and to gain further insights into the distributional properties of daily returns. A few recent studies have also employed these methods to examine the relative importance of jumps in terms of their magnitude, intensity and contribution to total price variation, and have extended techniques to identify the precise intraday timing, size and direction of jumps.

The availability of high frequency data has also prompted interesting studies in the market microstructure and market efficiency literatures. A stylised fact of these empirical studies finds that the largest intraday returns coincide with the announcement of macroeconomic information, showing dramatic reactions in returns and volatility following the arrival of public information. Moreover, price reactions are found to be statistically and economically significantly related to the informational surprise held within these announcements, with unexpected news explaining striking proportions of returns during these post announcement intervals. These results suggest extreme short term price reactions and confirm that asset prices are strongly linked to economic fundamentals in immediate response to macroeconomic news innovations. This chapter combines and contributes to these three strands of the recent financial econometrics literature. Within the framework of a continuous-time jump-diffusion log-price model, this study applies very recent non-parametric methods for detecting statistically significant asset price jumps, which rely on the availability of high frequency data only, to investigate the relationships between jumps and macroeconomic news announcements, thereby offering economic explanations for these jumps.

The main findings of the chapter are as follows. First, consistent across nine futures markets, covering foreign exchange, equity index and interest rate futures from the US, UK and Europe, and across a range of jump detection measures, jumps are shown to be an important component of the price process, thus rejecting the possibility that prices follow a purely continuous sample path. At the daily level, jumps occur far more frequently than would be expected from a continuous sample path diffusion process and far more frequently than parametric studies currently suggest. When jumps occur, they tend to be large, contribute heavily to total variation, and exhibit dynamic dependence suggesting that they may be partly predictable. Second, these findings are supported at the intraday level, with jumps associated with extreme five-minute returns which contribute substantive proportions of total daily variation, and these results are robust to the annihilation of the inherent intraday volatility patterns and alternative intraday jump detection procedures. Third, and offering the more innovative and interesting contribution of this work, many jumps coincide with the release of macroeconomic news. The analysis shows that the absolute values of jumps are significantly higher when US macroeconomic news is announced, showing pure announcement effects. Although this is restricted to isolated news events for some indicators, announcements of Consumer Confidence, GDP Advance, Initial Claims, ISM Index, Retail Sales, Trade Balance, FOMC interest rate decisions and especially the Employment Report cause numerous jumps.

Finally, intraday jumps that are caused by US macroeconomic news announcements are significantly related to the unexpected component of the announcement as measured by standardised news. Moreover, this information surprise explains staggering proportions of these intraday jumps, demonstrating the economic significance of the relationships between jumps and news and confirming the strength and importance of the links between short run price reactions and economic fundamentals.

There is a wealth of research that could be undertaken in future. Most obviously, this chapter excludes macroeconomic announcements from the UK and Europe since previous literature and preliminary data analysis suggest that they are dominated by their US counterparts. Of course, corroboration of this claim requires more robust treatment. More interesting, perhaps, would be an investigation of the asymmetric effects of news on jumps across business cycle conditions, as advocated recently by Andersen, Bollerslev, Diebold and Vega (2007) for international stock index futures. Alternatively, empirical work could make use of data sampled at higher frequencies than the five-minute data employed here to provide a richer investigation of intraday jumps and the response of asset prices to news announcements, although this would inevitably have to compensate for the associated market microstructure affects that would arise. This line of enquiry could also take advantage of the separation of continuous and jump components of the price process to investigate the transmission of both components of volatility across asset classes and geographic locations. Finally, since the arrival of public information does not explain the occurrence and magnitude of all intraday jumps, future work could make use of signed order flow (Evans and Lyons, 2002, 2005, Love and Payne, 2007), which proxies for private information held by market participants, to investigate another possible economic explanation of jumps.

CHAPTER 5

CONCLUSION

5.1 INTRODUCTION

The interdependence between financial markets and economic fundamentals has occupied a central role in research in financial economics for many years, dating back at least three decades. More recently, the availability of high frequency data has allowed the close examination of immediate and short lived linkages between asset returns, volatility, and macroeconomic news announcements. These developments have spurred new empirical literatures in market microstructure, financial econometrics and non-parametric analysis that have enabled an improved understanding of the distributional properties of asset returns and volatility dynamics, which is critical for asset and derivative pricing, portfolio allocation, risk management and forecasting. This thesis builds on these advances by further investigating the relationships between macroeconomic news announcements and financial markets in three independent contexts. Although each empirical chapter may be viewed independently, the unifying theme running throughout this thesis is the investigation of the responses of financial markets to macroeconomic news announcements, which are important to both investors and policy makers.

5.2 SUMMARY OF FINDINGS

The main objectives of the sub-discipline of asset pricing are to understand and explain the cross-section of historical asset returns in order to predict accurately expected asset returns. The Arbitrage Pricing Theory (APT) provides both an important development in this area and an alternative asset pricing model to the traditional CAPM, allowing asset returns to be generated by an arbitrary number of risk factors. The first empirical analysis reported in Chapter 2 is considered with a test of the APT using UK monthly stock returns and economic variables as potential risk factors, thereby jointly allowing the testing of APT as an asset pricing model and the identification of appropriate risk factors. It is found that the fully-revised macroeconomic data that are widely available and have conventionally been used in empirical finance research imply that macroeconomic variables are not important for the pricing of stocks. However, more encouragingly, the use of real-time data that measure more accurately the informational flow to the stock market reveals that unexpected inflation and economic uncertainty are indeed important factors for asset pricing. Inflation shocks and a more uncertain investment climate can be interpreted as systematic risk factors that are rewarded by the stock market, which have predictive power over future expected stock returns. The importance of this result is that the relationship between macroeconomic variables and stock returns are very sensitive to the type of macroeconomic data used. In an interesting extension of the initial analysis reported in Chapter 2, real-time pricing relationships are revealed to be asymmetric over the business cycle. During periods of economic expansion, inflationary shocks are more prevalent than investment uncertainty and are found to be the sole risk factor influencing expected stock returns. In contrast, when the economy is contracting and the risk of bankruptcies rises, investment uncertainty becomes the most important risk factor for pricing stocks. These findings are important for portfolio allocation decisions, risk management and portfolio hedging procedures and in helping to understand the risk-return trade off for asset pricing. The stock market reaction to UK macroeconomic surprises is also important for policy makers in understanding the asymmetric relationship between the stock market and economic fundamentals over the business cycle.

The understanding, measurement and forecasting of financial market volatility arguably constitute the most important issues in financial economics and have received considerable research attention in recent decades. The characterisation of the price discovery process, involving investigation of the way in which news about macroeconomic fundamentals is incorporated into asset prices, is also a central issue within the market efficiency and market microstructure literatures, but has enjoyed limited empirical success. In recent years, research focused on these core areas of finance has benefited greatly from the availability of high frequency financial data. It has been well documented that volatility is driven by three components: a distinctive, inherent intraday volatility pattern; macroeconomic news announcements; and a latent volatility factor often characterised by clustering and persistence at low frequencies. The components of high frequency returns volatility are not only significant in statistical and economic terms and interesting in their own right, but the identification and accurate modelling of their dynamics are also crucial in order to conduct a robust investigation of the response of returns to news announcements.

Chapter 3 addressed these concepts jointly by investigating the short-run reaction of Euro exchange rate returns and returns volatility to macroeconomic news announcements. Using a nineteen-month sample of five-minute returns for three Euro exchange rates, and therefore a new market setting, the analysis of Chapter 3 confirms a twenty-four hour pattern for intraday volatility, with volatility rising at the opening and overlapping of trading activity in the world's major financial centres, and reports that the largest five-minute returns are found to coincide with the release of macroeconomic news. Further, whilst previous studies of this type filter intraday volatility by fitting a flexible Fourier form (FFF) to the intraday pattern, Chapter 3 compares the performance of the FFF with an alternative cubic spline approach. Both specifications, in general, provide an excellent fit to the average intraday volatility pattern and capture the daily periodicity in the time series dependencies so as to highlight long memory as an inherent feature of high frequency returns volatility. Measurement of the response of volatility to macroeconomic news announcements, however, is found to be sensitive to the econometric framework applied, with the FFF often understating their effects compared to the cubic splines.

The largest reactions of volatility across the three rates are found to occur in response to US news. In a period of poor global economic performance, the decisions of the FOMC regarding US interest rates generate the largest instantaneous jumps in volatility and often the largest cumulative response over the period immediately following the announcement. Interest rate decisions by the ECB also feature prominently showing that monetary policy decisions are an important source of exchange rate volatility over the sample. In confirmation of previous studies, indicators of real activity such as the US Employment Report and GDP cause dramatic price reactions, whilst similar measures for the UK (including UK Industrial Production), Eurozone, Germany and Japan are among the highest ranking non-US announcements. The US Trade

Balance is also important, causing a larger reaction than US inflation data. Aside from such traditional macroeconomic information, forward looking indicators and regional economic surveys play a crucial and interesting role. These releases include the Philadelphia Federal Reserve Index, University of Michigan Consumer Sentiment Index, Chicago Purchasing Managers Index, Consumer Confidence Index and Institute of Supply Management Index for the US, and the IFO Business Expectations Index for Germany. Their release timing is such that they are the first indicators of macroeconomic performance for a particular month that traders observe, and data surprises are likely to generate larger price reactions.

Exchange rate returns are found to react very quickly to macroeconomic surprises, specifically, within five minutes of the release. With very little reaction thereafter, the immediate behaviour of returns can be described as conditional mean jumps. Furthermore, within the five-minute interval containing the announcement, macroeconomic innovations explain large proportions of the jumps. The largest jumps follow US news with unexpected strengthening of the US economy causing the Euro to depreciate, and against the US Dollar in particular. Construction Spending, Consumer Confidence, Durable Goods Orders, GDP Advance, GDP Preliminary, ISM Index (Manufacturing), Leading Indicators, Non-Farm Payrolls, Philadelphia Federal Reserve Index, Retail Sales, Trade Balance, Unemployment Rate and Initial Claims are all important announcements form the US, whilst Labour Costs Revised for the Eurozone, IFO Business Expectations and ZEW Expectations for Germany, and Trade Balance, GDP Preliminary, Industrial Production, Manufacturing Output, Retail Sales, RPI and RPIX for the UK are the non-US announcements influencing exchange rate returns. Interestingly, despite causing large responses in returns volatility, the large jumps in returns following interest rate decisions do not appear to be correlated with the informational surprise surrounding their announcement. These findings regarding return and volatility reactions to macroeconomic news announcements are important for traders with short intraday horizons, and confirm our understanding of volatility dynamics and are helpful for economic policy makers in anticipating likely reactions of financial markets to announcements.

The distributional properties of asset returns and the dynamics of return volatility have remained two very popular areas of research in financial economics over the last three decades, making important contributions to our understanding of the risk-return trade-off that is crucial for asset and derivative pricing, portfolio allocation and risk management techniques. Arguably, the most important developments along these lines have been based on continuous-time theory and methods and the latest research suggests that the incorporation of discontinuities, or jumps, and stochastic volatility is essential in accommodating the empirical regularities of extreme returns causing fat-tailed distributions, and temporal dependence, clustering, persistence and feedback effects in volatility. In parallel with the development of the parametric continuous-time literature, powerful non-parametric techniques have been advanced recently that rely solely on the availability of high frequency asset price data, which has become easily accessible over the last decade. The resulting literature concerning measuring and forecasting realised volatility has grown to become a substantive contribution to financial economic research. Combining these non-parametric techniques with the continuous-time framework, the most recent research provides the ability to separate continuous and discontinuous components of quadratic variation, which have been used to improve forecasting performance of daily volatility, and to gain further insights into the distributional properties of daily returns. A few recent studies have also employed these methods to examine the relative importance of jumps in terms of their magnitude, intensity and contribution to total price variation, and have extended the techniques to identify the precise intraday timing, size and direction of jumps. The availability of high frequency data has also prompted interesting studies in the market microstructure and market efficiency literatures. A stylised fact of these empirical studies finds that the largest intraday returns coincide with the announcement of macroeconomic information, showing dramatic reactions in returns and volatility following the arrival of public information. In light of these findings, the analysis presented in Chapter 4 implements a continuous-time jump-diffusion log-price model as the foundation for an investigation into financial market jumps.

The empirical analysis reported in Chapter 4 combines and contributes to the three strands of the recent financial econometrics literature described above. Within the framework of a continuous-time jump-diffusion log-price model, recent non-parametric methods for detecting statistically significant asset price jumps, which rely on the availability of high frequency data only, are applied in order to investigate the relationships between jumps and macroeconomic news announcements, thereby seeking to offer economic explanations for these jumps. The main findings of Chapter 4 are as follows. First, consistently across nine futures markets, covering foreign exchange, equity index and interest rate futures from the US, UK and Europe, and across a range of jump detection measures, jumps are shown to be an important component of the price process, thus rejecting the possibility that prices follow a purely continuous sample path. At the daily level, jumps occur far more frequently than would be expected from a continuous sample path diffusion process and far more frequently than parametric studies currently allow. When jumps occur, they tend to be large, contribute heavily to total variation and exhibit dynamic dependence suggesting that they may be partly predictable. Second, these findings are supported at the intraday level with jumps associated with extreme five-minute returns, which contribute substantive proportions of total daily variation, and these results are robust to the annihilation of the inherent intraday volatility patterns and alternative intraday jump detection procedures. Third, and offering an innovative and interesting contribution, many jumps coincide with the release of macroeconomic news. The analysis in Chapter 4 also shows that the absolute values of jumps are significantly higher when US macroeconomic news is announced, showing pure announcement effects. Although this is restricted to isolated news events for some indicators, announcements of Consumer Confidence, GDP Advance, Initial Claims, ISM Index, Retail Sales, Trade Balance, FOMC interest rate decisions and especially the Employment Report, cause numerous jumps. Intraday jumps that are caused by US macroeconomic news announcements are significantly related to the unexpected component of the announcement as measured by standardised news. Moreover, this information surprise explains staggering proportions of these intraday jumps, demonstrating the economic significance of the relationships between jumps and news and confirming the strength and importance of the links between short-run price reactions and economic fundamentals.

5.3 FURTHER RESEARCH

The empirical findings reported in this thesis confirm the presence of important relationships between financial markets and macroeconomic news announcements that provide important and interesting contributions to the financial economics literature. In addition, the results are of practical relevance for asset and derivative pricing, portfolio allocation, risk management, hedging, financial forecasting and economic policy.

The findings reported in this thesis provide numerous directions for potential future research. The analysis in Chapter 2, for example, may be extended by using higher frequency data to isolate more immediate effects of news releases as risk factors, whilst the crucial role of unanticipated inflation identified might also prompt further investigation of the links between asset markets and monetary policy. An interesting extension to the econometric techniques employed in Chapter 2 could advance the modelling of economic expectations and the separation of economic expansion and contraction periods across the business cycle. Further research might also pay more attention to the statistical inference of estimated coefficients rather than to their averages, particularly for the estimated sensitivities of risk factors.

Given the importance of the discovery of asymmetric risk pricing in Chapter 2, it would be interesting to extend the sample used in Chapter 3 to cover different phases of the business cycle in order to analyse whether Euro exchange rates react symmetrically to good and bad news and whether this reaction is symmetric during economic expansions and contractions. The importance of monetary policy decisions identified in Chapter 3 suggests that it would be particularly interesting to relate possible asymmetric news effects to the reaction functions of monetary policy authorities, which may help to explain why some announcements are particularly important. Further research might also attempt to explain why macroeconomic news announcement effects impart such different dynamics on returns compared to volatility, investigate macroeconomic news effects in returns and volatility across time horizons, and seek to associate the violent price reactions with trading volume and private information.

The obvious extensions to Chapter 4 would be to investigate the possible asymmetric effects of news on jumps across business cycle conditions, which might also involve a thorough treatment of non-US macroeconomic news announcements, particularly for the UK and European markets. Alternatively, future empirical work could make use of data sampled at higher frequencies than the five-minute data employed in Chapter 4 to provide a richer investigation of intraday jumps and the response of asset prices to news announcements. This line of enquiry would also have the advantage of allowing the separation of continuous and jump components of the price process in order to investigate the transmission of volatility components and information across asset classes and geographic locations, and preferably within a multivariate framework. Finally, since the arrival of public information does not explain the occurrence and magnitude of all intraday jumps, future work could also examine whether the private information held by market participants provides an alternative economic explanation for jumps.

APPENDICES

A.1 APPENDIX 1

Tables A.1.1 to A.1.3 show the estimation results for equation (3.5) using equations (3.11) and (3.12) for the intraday pattern and using different specifications for the daily volatility factor.

A.2 APPENDIX 2

Tables A.2.1 to A.2.6 show the coefficient estimates for macroeconomic news announcements whose loading coefficient was not significantly different from zero.

Table A.1.1. Intraday Patterns and Calendar Effects Using Sample Mean MA(1)-FIGARCH(1,d,1) Daily Volatility Factor.

Panel (A) Intraday Patterns

	FFF				SPLINE		
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
$\hat{\mu}_0 + \mu_1$	**-2.532**	**-2.360**	**-2.365**	$\hat{\mu}_0 + \mu_1$	**-3.119**	**-2.935**	**-2.931**
	(-51.13)	(-42.77)	(-44.44)		(-17.66)	(-14.28)	(-17.08)
$\delta_{cos,1}$	**-0.277**	**-0.229**	**-0.213**	$\alpha_{1,1}$	8.404	12.480	12.522
	(-10.59)	(-7.77)	(-7.62)		(0.88)	(1.04)	(1.28)
$\delta_{cos,2}$	**-0.090**	**0.077**	-0.043	$\alpha_{2,1}$	-313.69	-194.30	-298.45
	(-3.52)	(2.63)	(-1.58)		(-1.92)	(-0.95)	(-1.73)
$\delta_{cos,3}$	**-0.287**	**-0.277**	**-0.289**	$\alpha_{3,1}$	**2168.5**	879.78	**1942.4**
	(-11.69)	(-9.71)	(-10.83)		(2.68)	(0.88)	(2.27)
$\delta_{cos,4}$	**0.116**	0.036	0.039	$\alpha_{1,2}$	**-36.211**	-11.630	**-35.654**
	(4.95)	(1.31)	(1.53)		(-4.49)	(-1.25)	(-4.39)
$\delta_{sin,1}$	**-0.607**	**-0.648**	**-0.430**	$\alpha_{2,2}$	**-488.92**	-115.89	**-415.04**
	(-23.87)	(-22.20)	(-15.45)		(-3.37)	(-0.66)	(-2.73)
$\delta_{sin,2}$	**-0.133**	0.005	0.017	$\alpha_{3,2}$	**-2174.6**	-893.32	**-1952.5**
	(5.36)	(0.18)	(0.64)		(-2.68)	(-0.89)	(-2.28)
$\delta_{sin,3}$	**0.144**	**0.159**	**0.100**	$\alpha_{1,3}$	4.885	3.398	-1.227
	(5.94)	(5.80)	(3.75)		(0.82)	(0.47)	(-0.19)
$\delta_{sin,4}$	**-0.110**	-0.046	**-0.095**	$\alpha_{2,3}$	114.82	182.10	**261.07**
	(4.73)	(-1.17)	(-3.81)		(1.04)	(1.34)	(2.12)
				$\alpha_{3,3}$	-398.52	-865.15	-1287.2
					(-0.67)	(-1.21)	(-1.96)
				$\alpha_{1,4}$	**-26.195**	-15.971	-8.331
					(-3.50)	(-1.82)	(-0.98)
				$\alpha_{2,4}$	76.070	158.15	235.59
					(0.69)	(1.19)	(1.91)
				$\alpha_{3,4}$	380.73	866.33	1289.1
					(0.63)	(1.19)	(1.92)
				$\alpha_{1,5}$	-8.290	1.602	0.879
					(-1.78)	(0.31)	(0.18)
				$\alpha_{2,5}$	**-96.023**	**-109.87**	**-98.249**
					(-3.70)	(-3.74)	(-3.57)
				$\alpha_{3,5}$	**179.29**	**231.28**	**203.37**
					(2.23)	(2.54)	(2.38)

Table A.1.1. (Continued)

Panel (B) Calendar Effects							
		FFF				SPLINE	
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
Tokyo	**0.504**	**0.485**	**0.633**	Tokyo	0.215	**0.456**	**0.398**
	(4.19)	(3.12)	(5.02)		(1.64)	(2.65)	(2.92)
Hong Kong	0.224	0.230	**0.431**	Hong Kong	**0.224**	0.277	**0.458**
	(1.92)	(1.53)	(3.62)		(1.98)	(1.89)	(4.01)
Holiday	**-0.278**	-0.120	**-0.144**	Holiday	**-0.276**	-0.113	**-0.141**
	(-4.30)	(-1.61)	(-2.14)		(-4.30)	(-1.54)	(-2.08)
US News	**0.997**	**0.989**	**1.024**	US News	**0.997**	**0.989**	**1.024**
	(9.87)	(5.37)	(5.91)		(10.17)	(5.58)	(6.15)
Monday	-0.195	0.108	-0.274	Monday	-0.291	0.190	-0.351
Early	(-0.79)	(0.42)	(-1.07)	Early	(-1.14)	(0.65)	(-1.24)
	0.036	0.059	-0.006		0.037	0.030	-0.007
	(0.79)	(1.31)	(-0.14)		(0.77)	(0.58)	(-0.14)
Friday	-0.010	-0.001	-0.011	Friday	-0.009	0.001	-0.007
Late	(-0.88)	(-0.06)	(-0.88)	Late	(-0.75)	(0.08)	(-0.55)
	0.000	0.000	0.000		0.000	0.000	0.000
	(0.89)	(0.53)	(1.33)		(0.81)	(0.41)	(0.97)
Winter	**-0.429**			Winter	**-0.526**		
Slowdown	(-2.35)			Slowdown	(-2.46)		
	0.021				0.031		
	(0.95)				(1.26)		
Summer	**-0.045**	-0.016	0.001	Summer	-0.032	-0.015	-0.013
Slowdown	(-2.37)	(-0.70)	(0.06)	Slowdown	(-1.45)	(-0.55)	(-0.58)
Summer	**0.298**	**0.210**	0.026	Summer	**0.314**	**0.228**	-0.007
	(8.15)	(5.21)	(0.68)		(4.52)	(3.28)	(-0.10)
Tuesday	**0.348**	**0.295**	**0.362**	Tuesday	**0.343**	**0.291**	**0.358**
	(6.24)	(4.66)	(6.08)		(6.15)	(4.59)	(5.99)
Wednesday	**0.164**	0.075	0.119	Wednesday	**0.159**	0.072	0.115
	(2.49)	(1.03)	(1.65)		(2.42)	(0.97)	(1.59)
Thursday	**0.379**	**0.341**	**0.362**	Thursday	**0.372**	**0.336**	**0.357**
	(6.78)	(5.39)	(6.07)		(6.66)	(5.31)	(5.98)
Friday	0.134	0.089	0.095	Friday	0.122	0.079	0.086
	(1.92)	(1.16)	(1.23)		(1.74)	(1.03)	(1.10)

Notes: The table reports the estimated coefficients and their Newey and West (1987) robust *t* statistics shown in parentheses for equation (3.5), using equations (3.11) and (3.12) as alternative specifications for the intraday volatility pattern. Returns are calculated from five-minute logarithmic average bid-ask quotes from 2nd January 2002 to 31st July 2003. Quotes from Friday 21:05 to Sunday 21:00 are excluded giving 118, 656 observations. The absolute value of de-meaned five-minute returns is standardised by a daily volatility factor calculated as the sample mean of conditional volatility obtained from a MA(1)-FIGARCH(1,d,1) model fitted to a longer daily sample of spot exchange rates from 2nd January 1999 to 31st July 2003 as specified by equations (3.8), (3.9) and (3.10). Bold denotes coefficients statistically significant at a minimum 5% level.

Table A.1.2. Intraday Patterns and Calendar Effects Using MA(1)-GARCH(1,1) Daily Volatility Factor.

Panel (A) Intraday Patterns							
		FFF				SPLINE	
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
$\hat{\mu}_0 + \mu_1$	**-2.542**	**-2.210**	**-2.110**	$\hat{\mu}_0 + \mu_1$	**-3.128**	**-2.784**	**-2.676**
	(-51.26)	(-40.68)	(-39.48)		(-17.71)	(-13.69)	(-15.54)
$\delta_{cos,1}$	**-0.277**	**-0.229**	**-0.213**	$\alpha_{1,1}$	8.404	12.454	12.521
	(-10.57)	(-7.92)	(-7.63)		(0.88)	(1.05)	(1.28)
$\delta_{cos,2}$	**-0.090**	**0.078**	-0.043	$\alpha_{2,1}$	-313.68	-193.67	-298.47
	(-3.52)	(2.73)	(-1.56)		(-1.92)	(-0.95)	(-1.73)
$\delta_{cos,3}$	**-0.287**	**-0.277**	**-0.289**	$\alpha_{3,1}$	**2168.5**	875.45	**1941.9**
	(-11.68)	(-9.89)	(-10.85)		(2.68)	(0.88)	(2.28)
$\delta_{cos,4}$	**0.116**	0.036	0.040	$\alpha_{1,2}$	**-36.211**	-11.573	**-35.634**
	(4.95)	(1.33)	(1.54)		(-4.49)	(-1.25)	(-4.39)
$\delta_{sin,1}$	**-0.607**	**-0.649**	**-0.431**	$\alpha_{2,2}$	**-488.91**	-114.80	**-414.77**
	(-23.84)	(-22.64)	(-15.52)		(-3.37)	(-0.66)	(-2.74)
$\delta_{sin,2}$	**-0.133**	0.005	0.017	$\alpha_{3,2}$	**-2174.6**	-889.07	**-1952.1**
	(-5.35)	(0.185)	(0.64)		(-2.68)	(-0.89)	(2.29)
$\delta_{sin,3}$	**0.144**	**0.159**	**0.098**	$\alpha_{1,3}$	4.886	3.356	-1.251
	(5.93)	(5.90)	(3.77)		(0.82)	(0.47)	(-0.19)
$\delta_{sin,4}$	**-0.110**	-0.046	**-0.095**	$\alpha_{2,3}$	114.80	183.25	261.72
	(-4.73)	(-1.75)	(-3.82)		(1.04)	(1.36)	(2.13)
				$\alpha_{3,3}$	-398.39	-871.74	**-1290.8**
					(-0.67)	(-1.23)	(-1.96)
				$\alpha_{1,4}$	**-26.195**	-15.904	-8.306
					(-3.49)	(-1.84)	(-0.98)
				$\alpha_{2,4}$	76.046	159.27	236.22
					(0.69)	(1.21)	(1.91)
				$\alpha_{3,4}$	380.58	873.33	1293.1
					(0.63)	(1.21)	(1.93)
				$\alpha_{1,5}$	-8.287	1.632	0.829
					(-1.78)	(0.32)	(0.17)
				$\alpha_{2,5}$	**-96.033**	**-110.06**	**-98.230**
					(-3.70)	(-3.82)	(-3.57)
				$\alpha_{3,5}$	**179.33**	**231.19**	**203.06**
					(2.22)	(2.58)	(2.37)

Table A.1.2. (Continued)

Panel (B) Calendar Effects							
		FFF				SPLINE	
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
Tokyo	**0.504**	**0.484**	**0.633**	Tokyo	0.215	**0.456**	**0.398**
	(4.19)	(3.13)	(5.05)		(1.64)	(2.66)	(2.93)
Hong Kong	0.224	0.230	**0.431**	Hong Kong	**0.224**	0.278	**0.458**
	(1.92)	(1.55)	(3.64)		(1.98)	(1.91)	(4.03)
Holiday	**-0.280**	-0.035	-0.087	Holiday	**-0.278**	-0.028	-0.083
	(-4.33)	(-0.47)	(-1.25)		(-4.33)	(-0.38)	(-1.20)
US News	**0.998**	**0.999**	**1.011**	US News	**0.998**	**0.999**	**1.011**
	(9.87)	(5.47)	(5.85)		(10.16)	(5.68)	(6.08)
Monday	-0.195	0.108	-0.274	Monday	-0.291	0.190	-0.351
Early	(-0.79)	(0.43)	(-1.04)	Early	(-1.14)	(0.66)	(-1.21)
	0.036	0.060	-0.007		0.037	0.029	-0.008
	(0.78)	(1.28)	(-0.15)		(0.77)	(0.56)	(-0.15)
Friday	-0.010	-0.001	-0.011	Friday	-0.009	0.001	-0.007
Late	(-0.88)	(-0.07)	(-0.88)	Late	(-0.75)	(0.07)	(-0.55)
	0.000	0.000	0.000		0.000	0.000	0.000
	(0.89)	(0.55)	(1.33)		(0.81)	(0.42)	(0.97)
Winter	**-0.429**			Winter	**-0.526**		
Slowdown	(-2.35)			Slowdown	(-2.46)		
	0.021				0.031		
	(0.95)				(1.25)		
Summer	**-0.045**	-0.016	0.001	Summer	-0.032	-0.015	-0.014
Slowdown	(-2.37)	(-0.72)	(0.06)	Slowdown	(-1.45)	(-0.57)	(-0.59)
Summer	**0.303**	**0.137**	**0.099**	Summer	**0.318**	**0.155**	0.066
	(8.25)	(3.46)	(2.56)		(4.57)	(2.26)	(1.01)
Tuesday	**0.349**	**0.304**	**0.364**	Tuesday	**0.344**	**0.300**	**0.360**
	(6.25)	(4.93)	(6.09)		(6.15)	(4.85)	(6.00)
Wednesday	**0.165**	0.091	0.122	Wednesday	**0.160**	0.087	0.118
	(2.49)	(1.26)	(1.69)		(2.42)	(1.21)	(1.63)
Thursday	**0.379**	**0.345**	**0.366**	Thursday	**0.372**	**0.340**	**0.360**
	(6.78)	(5.59)	(6.11)		(6.66)	(5.50)	(6.01)
Friday	0.134	0.098	0.103	Friday	0.122	0.089	0.093
	(1.92)	(1.31)	(1.32)		(1.75)	(1.17)	(1.19)

Notes: The table reports the estimated coefficients and their Newey and West (1987) robust *t* statistics shown in parentheses for equation (3.5), using equations (3.11) and (3.12) as alternative specifications for the intraday volatility pattern. Returns are calculated from five-minute logarithmic average bid-ask quotes from 2nd January 2002 to 31st July 2003. Quotes from Friday 21:05 to Sunday 21:00 are excluded giving 118, 656 observations. The absolute value of de-meaned five-minute returns is standardised by a daily volatility factor obtained from a MA(1)-GARCH(1,1) model fitted to a longer daily sample of spot exchange rates from 2nd January 1999 to 31st July 2003 as specified by equations (3.7) and (3.9). Bold denotes coefficients statistically significant at a minimum 5% level.

Table A.1.3. Intraday Patterns and Calendar Effects Using Sample Mean MA(1)-GARCH(1,1) Daily Volatility Factor.

Panel (A) Intraday Patterns

	FFF					SPLINE	
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
$\hat{\mu}_0 + \mu_1$	**-2.539**	**-2.258**	**-2.073**	$\hat{\mu}_0 + \mu_1$	**-3.125**	**-2.833**	**-2.639**
	(-51.27)	(-40.93)	(-38.97)		(-17.70)	(-13.78)	(-15.38)
$\delta_{cos,1}$	**-0.277**	**-0.229**	**-0.213**	$\alpha_{1,1}$	8.404	12.480	12.522
	(-10.59)	(-7.77)	(-7.62)		(0.88)	(1.04)	(1.28)
$\delta_{cos,2}$	**-0.090**	**0.077**	-0.043	$\alpha_{2,1}$	-313.69	-194.30	-298.45
	(-3.52)	(2.64)	(-1.58)		(-1.92)	(-0.95)	(-1.73)
$\delta_{cos,3}$	**-0.287**	**-0.277**	**-0.289**	$\alpha_{3,1}$	**2168.5**	879.78	**1942.4**
	(-11.69)	(-9.71)	(-10.83)		(2.68)	(0.88)	(2.27)
$\delta_{cos,4}$	**0.116**	0.036	0.039	$\alpha_{1,2}$	**-36.211**	-11.630	**-35.654**
	(4.95)	(1.31)	(1.53)		(-4.49)	(-1.25)	(-4.39)
$\delta_{sin,1}$	**-0.607**	**-0.648**	**-0.430**	$\alpha_{2,2}$	**-488.92**	-115.79	**-415.04**
	(-23.87)	(-22.20)	(-15.45)		(-3.37)	(-0.66)	(-2.73)
$\delta_{sin,2}$	**-0.133**	0.005	0.017	$\alpha_{3,2}$	**-2174.6**	-893.32	**-1952.5**
	(-5.36)	(0.18)	(0.64)		(-2.68)	(-0.89)	(-2.28)
$\delta_{sin,3}$	**0.144**	**0.159**	**0.098**	$\alpha_{1,3}$	4.885	3.398	-1.227
	(5.94)	(5.80)	(3.75)		(0.82)	(0.47)	(-0.19)
$\delta_{sin,4}$	**-0.110**	-0.046	**-0.095**	$\alpha_{2,3}$	114.82	182.10	**261.07**
	(-4.73)	(-1.73)	(-3.82)		(1.04)	(1.34)	(2.12)
				$\alpha_{3,3}$	-398.52	-865.15	-1287.2
					(-0.67)	(-1.21)	(-1.95)
				$\alpha_{1,4}$	**-26.195**	-15.971	-8.331
					(-3.50)	(-1.82)	(-0.98)
				$\alpha_{2,4}$	76.070	158.15	235.59
					(0.69)	(1.19)	(1.90)
				$\alpha_{3,4}$	380.73	866.33	1289.1
					(0.63)	(1.19)	(1.92)
				$\alpha_{1,5}$	-8.290	1.602	0.879
					(1.78)	(0.31)	(0.18)
				$\alpha_{2,5}$	**-96.023**	**-109.87**	**-98.249**
					(-3.70)	(-3.74)	(-3.57)
				$\alpha_{3,5}$	**179.29**	**231.28**	**203.37**
					(2.23)	(2.54)	(2.38)

Table A.1.3. (Continued)

Panel (B) Calendar Effects							
		FFF				SPLINE	
COEFF	EUR-USD	EUR-GBP	EUR-JPY	COEFF	EUR-USD	EUR-GBP	EUR-JPY
Tokyo	0.504	0.485	**0.633**	Tokyo	0.215	**0.456**	**0.398**
	(4.19)	(3.12)	(5.02)		(1.64)	(2.65)	(2.92)
Hong Kong	0.224	0.230	**0.431**	Hong Kong	**0.224**	0.277	**0.458**
	(1.92)	(1.54)	(3.62)		(1.98)	(1.89)	(4.01)
Holiday	-0.278	-0.120	**-0.145**	Holiday	**-0.276**	-0.113	**-0.141**
	(-4.30)	(-1.61)	(-2.14)		(-4.30)	(-1.54)	(-2.08)
US News	0.997	**0.989**	**1.024**	US News	**0.997**	**0.989**	**1.024**
	(9.87)	(5.37)	(5.91)		(10.16)	(5.58)	(6.15)
Monday	-0.195	0.108	-0.274	Monday	-0.291	0.189	-0.351
Early	(-0.79)	(0.42)	(-1.07)	Early	(-1.14)	(0.65)	(-1.24)
	0.036	0.059	-0.006		0.037	0.030	-0.007
	(0.79)	(1.31)	(-0.14)		(0.77)	(0.58)	(-0.14)
Friday	-0.010	-0.001	-0.011	Friday	-0.009	0.001	-0.007
Late	(-0.88)	(-0.06)	(-0.88)	Late	(-0.75)	(0.08)	(-0.55)
	0.000	0.000	0.000		0.000	0.000	0.000
	(0.89)	(0.53)	(1.33)		(0.81)	(0.41)	(0.97)
Winter	-0.429			Winter	**-0.526**		
Slowdown	(-2.35)			Slowdown	(-2.46)		
	0.021				0.031		
	(0.95)				(1.26)		
Summer	**-0.045**	-0.016	0.001	Summer	-0.032	-0.015	-0.013
Slowdown	(-2.37)	(-0.70)	(0.06)	Slowdown	(-1.45)	(-0.55)	(-0.58)
Summer	**0.298**	**0.210**	0.026	Summer	**0.314**	**0.228**	-0.007
	(8.15)	(5.21)	(0.68)		(4.52)	(3.28)	(-0.10)
Tuesday	**0.348**	**0.295**	**0.362**	Tuesday	**0.343**	**0.291**	**0.358**
	(6.24)	(4.66)	(6.08)		(6.15)	(4.59)	(5.99)
Wednesday	**0.164**	0.075	0.119	Wednesday	**0.159**	0.072	0.115
	(2.49)	(1.03)	(1.65)		(2.42)	(0.97)	(1.59)
Thursday	**0.379**	**0.341**	**0.362**	Thursday	**0.372**	**0.336**	**0.357**
	(6.78)	(5.39)	(6.07)		(6.66)	(5.31)	(5.98)
Friday	0.134	0.089	0.095	Friday	0.122	0.079	0.086
	(1.92)	(1.16)	(1.23)		(1.74)	(1.03)	(1.10)

Notes: The table reports the estimated coefficients and their Newey and West (1987) robust *t* statistics shown in parentheses for equation (3.5), using equations (3.11) and (3.12) as alternative specifications for the intraday volatility pattern. Returns are calculated from five-minute logarithmic average bid-ask quotes from 2nd January 2002 to 31st July 2003. Quotes from Friday 21:05 to Sunday 21:00 are excluded giving 118, 656 observations. The absolute value of de-meaned five-minute returns is standardised by a daily volatility factor calculated as the sample mean of conditional volatility obtained from a MA(1)-GARCH(1,1) model fitted to a longer daily sample of spot exchange rates from 2nd January 1999 to 31st July 2003 as specified by equations (3.7), (3.9) and (3.10). Bold denotes coefficients statistically significant at a minimum 5% level.

Table A.2.1. Insignificant Announcement Effects for EUR-USD Using FFF Model.

ANNOUNCEMENT	COUNTRY	COEFF	ANNOUNCEMENT	COUNTRY	COEFF
Import Prices	GER	0.48	COL Final	GER	0.05
Housing Completions	US	0.39	Capital Account	GER	0.03
Unemployment	GER	0.48	M4 Provisional	UK	-0.02
Consumer Confidence	EU	0.54	GDP Final	UK	-0.03
Labour Costs Prelim.	EU	0.79	NAHB Housing Index	US	-0.05
Labour Costs Revised	EU	0.63	Consumer Credit	US	-0.05
Current Account	GER	0.38	Services Index	FRA	-0.04
Trade Balance	GER	0.38	Treasury Budget	US	-0.08
Industrial Production	FRA	0.29	Unemployment	FRA	-0.10
OECD Leading Indicators	EU	0.57	FX Reserves	JAP	-0.07
MPC Interest Rate	UK	0.34	GDP	GER	-0.18
Productivity Preliminary	US	0.50	Business Climate	FRA	-0.11
GDP Preliminary	EU	0.42	M2	US	-0.07
Business Climate Index	EU	0.35	Import Prices	US	-0.13
HCPI	EU	0.32	CPI	EU	-0.16
Employment	GER	0.35	CIPS Services	UK	-0.15
COL Preliminary	GER	0.34	CPI Final	FRA	-0.16
Manufacturing Orders	GER	0.36	Industrial Production	JAP	-0.30
Industrial Production	UK	0.40	Construction Orders	JAP	-0.32
ISM Manufacturing	US	0.56	GDP Preliminary	UK	-0.56
Dept. Store Sales	JAP	0.29	Current Account	EU	-0.19
BOJ Monetary Policy	JAP	0.33	Construction Spending	US	-0.25
Factory Inventories/Orders	US	0.24	Business Inventories	US	-0.21
GDP Final	US	0.23	Leading Indicators	US	-0.42
Services Index	GER	0.25	PMI	EU	-0.30
PPI	EU	0.24	HCPI	UK	-0.28
Personal Income	US	0.38	Supermarket Sales	JAP	-0.41
Trade Balance	FRA	0.21	Unemployment	UK	-0.22
CIPS Manufacturing	UK	0.22	PPI	FRA	-0.54
PSNCR	UK	0.18	Nationwide House Prices	UK	-0.33
Shipments	JAP	0.34	GDP Preliminary	FRA	-0.76
ZEW Expectations	GER	0.17	Trade Balance	UK	-0.16
ISM Non Manufacturing	US	0.92	CPI	JAP	-0.72
PMI	GER	0.14	Unemployment	EU	-0.48
Services Index	EU	0.10	IFO Manufacturing Survey	GER	-0.30
CPI Preliminary	FRA	0.12	PPI	UK	-0.56
M4 Final	UK	0.12	Coincident Index	JAP	-0.58
GDP Revised	JAP	0.23	Tankan Manuf. Survey	JAP	-2.34
Challenger Layoffs	US	0.10	Income	JAP	-0.87
Chicago Ntl. Activity Index	US	0.09	Unemployment	JAP	-0.94
Consumer Credit	UK	0.09	GDP Revised	EU	-1.15
Tertiary Index	JAP	0.09	Retail Sales	EU	-0.80
Tokyo Dept. Store Sales	JAP	0.05	INSEE Report	FRA	-2.54
PPI	GER	0.04	GDP Final	EU	-0.73
Trade Balance	JAP	0.06	GDP Final	FRA	-0.69

Table A.2.2. Insignificant Announcement Effects for EUR-USD Using Spline Model.

ANNOUNCEMENT	COUNTRY	COEFF	ANNOUNCEMENT	COUNTRY	COEFF
Non-Farm Payrolls Prelim.	FRA	0.65	Industrial Production	FRA	0.01
Employment	GER	0.52	Import Prices	US	0.00
Productivity Preliminary	US	0.62	Treasury Budget	US	-0.03
Trade Final	EU	0.42	COL Final	GER	-0.03
Services Index	GER	0.43	HCPI	UK	-0.05
Industrial Production	UK	0.57	Trade Balance	FRA	-0.05
PSNCR	UK	0.35	Unemployment	UK	-0.04
Import Prices	GER	0.34	NAHB Housing Index	US	-0.09
CIPS Manufacturing	UK	0.38	PMI	EU	-0.08
Consumer Confidence	EU	0.40	Tertiary Index	JAP	-0.09
Services Index	EU	0.29	Current Account	EU	-0.09
PMI	GER	0.32	PPI	GER	-0.07
BOJ Monetary Policy	JAP	0.38	Business Inventories	US	-0.10
GDP Final	US	0.29	Trade Balance	JAP	-0.12
M4 Final	UK	0.31	GDP Preliminary	UK	-0.35
Consumer Credit	UK	0.28	Construction Orders	JAP	-0.20
Labour Costs Revised	EU	0.47	CPI Preliminary	FRA	-0.13
Labour Costs Prelim.	EU	0.56	GDP	GER	-0.29
OECD Leading Indicators	EU	0.42	Construction Spending	US	-0.22
Dept. Store Sales	JAP	0.28	Supermarket Sales	JAP	-0.30
Current Account	GER	0.25	CPI	EU	-0.26
Trade Balance	GER	0.25	Industrial Production	JAP	-0.40
MPC Interest Rate	UK	0.24	M2	US	-0.16
Household Survey	FRA	0.24	FX Reserves	JAP	-0.21
ZEW Expectations	GER	0.26	Unemployment	FRA	-0.37
Personal Income	US	0.45	Leading Indicators	US	-0.45
ISM Manufacturing	US	0.47	PPI	UK	-0.36
COL Preliminary	GER	0.27	Business Climate	FRA	-0.35
Household Consumption	FRA	0.17	IFO Manufacturing Survey	GER	-0.24
Factory Inventories/Orders	US	0.19	Coincident Index	JAP	-0.47
Manufacturing Orders	GER	0.26	CPI	JAP	-0.74
Business Climate Index	EU	0.21	CPI Final	FRA	-0.42
GDP Preliminary	EU	0.24	Nationwide House Prices	UK	-0.41
HCPI	EU	0.20	PPI	FRA	-0.77
M4 Provisional	UK	0.18	GDP Preliminary	FRA	-1.02
Services Index	FRA	0.15	Income	JAP	-0.88
Tokyo Dept. Store Sales	JAP	0.11	Tankan Manuf. Survey	JAP	-2.48
GDP Final	UK	0.18	Unemployment	JAP	-0.95
PPI	EU	0.09	Unemployment	EU	-0.59
Capital Account	GER	0.08	Trade Balance	UK	-0.26
Shipments	JAP	0.13	GDP Final	EU	-0.61
CIPS Services	UK	0.06	GDP Revised	EU	-1.20
Challenger Layoffs	US	0.05	INSEE Report	FRA	-2.44
Chicago Ntl. Activity Index	US	0.04	Retail Sales	EU	-0.89
Consumer Credit	US	0.02	GDP Final	FRA	-0.64
GDP Revised	JAP	0.04			

Table A.2.3. Insignificant Announcement Effects for EUR-GBP Using FFF Model.

ANNOUNCEMENT	COUNTRY	COEFF	ANNOUNCEMENT	COUNTRY	COEFF
Industrial Production	EU	0.70	Current Account	EU	0.03
GDP Preliminary	FRA	1.87	M2	JAP	-0.02
Consumer Confidence	US	0.72	Halifax House Prices	UK	-0.04
ZEW Expectations	GER	0.74	Labour Costs Prelim.	EU	-0.18
Household Survey	FRA	0.79	PPI	FRA	-0.16
COL Preliminary	GER	0.76	GDP Revised	EU	-0.41
Nationwide House Prices	UK	0.68	Services Index	FRA	-0.16
CPI	EU	0.70	Supermarket Sales	JAP	-0.13
Unemployment	EU	0.67	GDP Final	US	-0.28
Retail Sales	GER	0.70	PMI	FRA	-0.21
M2	US	0.44	Tertiary Index	JAP	-0.16
Philadelphia Fed. Index	US	0.88	Shipments	JAP	-0.26
Consumer Confidence	JAP	0.43	Services Index	GER	-0.27
ISM Manufacturing	US	1.13	Capital Account	GER	-0.31
Dept. Store Sales	JAP	0.39	GDP Preliminary	UK	-0.28
Retail Sales	EU	0.66	PMI	GER	-0.35
Business Climate Index	EU	0.42	Existing Home Sales	US	-0.34
M4 Final	UK	0.49	Construction Spending	US	-0.45
Unemployment	FRA	0.75	Industrial Production	JAP	-0.38
Consumer Confidence	UK	0.45	GDP Final	FRA	-0.34
Unemployment	GER	0.46	PMI	EU	-0.49
Trade Balance	US	0.48	GDP	JAP	-0.78
Current Account	GER	0.45	Leading Indicators	US	-0.67
Trade Balance	GER	0.45	Trade Balance	JAP	-0.32
Chicago PMI	US	0.51	Current Account	FRA	-0.55
CPI Final	FRA	0.34	Chicago Ntl. Activity Index	US	-0.58
CPI Preliminary	FRA	0.42	Services Index	EU	-0.75
OECD Leading Indicators	EU	0.66	PPI	UK	-0.65
Business Climate	FRA	0.32	Employment	GER	-0.66
Household Consumption	FRA	0.32	Industrial Production	GER	-0.47
Consumer Credit	UK	0.27	New Home Sales	US	-0.85
NAHB Housing Index	US	0.25	Income	JAP	-0.78
Consumer Credit	US	0.33	Tokyo Dept. Store Sales	JAP	-0.47
Coincident Index	JAP	0.23	IFO Manufacturing Survey	GER	-0.85
Factory Inventories/Orders	US	0.29	Business Inventories	US	-0.97
GDP Revised	JAP	0.28	CPI	JAP	-0.88
Labour Costs Final	EU	0.47	Unemployment	JAP	-0.94
CIPS Manufacturing	UK	0.20	Treasury Budget	US	-1.37
PPI	US	0.19	Construction Orders	JAP	-1.10
GDP Provisional	UK	0.38	Challenger Layoffs	US	-0.99
Manufacturing Orders	GER	0.16	PSNCR	UK	-0.90
Productivity Preliminary	US	0.53	Tankan Manuf. Survey	JAP	-2.82
Import Prices	US	0.13	Trade Balance	UK	-0.87
Retail Sales	JAP	0.12	INSEE Report	FRA	-4.38
Productivity Revised	US	0.15	M4 Provisional	UK	-1.21
Current Account	US	0.14	GDP Final	EU	-1.86
Housing Completions	US	0.05	CPI	US	-1.89
Personal Income	US	0.07	FX Reserves	JAP	-1.34
HCPI	UK	0.03			

Table A.2.4. Insignificant Announcement Effects for EUR-GBP Using Spline Model.

ANNOUNCEMENT	COUNTRY	COEFF	ANNOUNCEMENT	COUNTRY	COEFF
ZEW Expectations	GER	0.85	Services Index	FRA	0.09
Non-Farm Payrolls Final	FRA	1.13	Current Account	US	0.14
Trade Balance	FRA	0.96	Personal Income	US	0.10
Industrial Production	EU	0.59	Services Index	GER	0.03
Consumer Confidence	US	0.69	CPI Preliminary	FRA	-0.01
Industrial Production	FRA	0.83	PMI	FRA	-0.03
M4 Final	UK	0.76	Labour Costs Prelim.	EU	-0.16
COL Preliminary	GER	0.76	PMI	GER	-0.16
Consumer Confidence	JAP	0.75	CPI Final	FRA	-0.12
CPI	EU	0.64	Business Climate	FRA	-0.13
Import Prices	GER	0.61	Industrial Production	JAP	-0.26
Philadelphia Fed. Index	US	0.80	Household Consumption	FRA	-0.14
GDP Preliminary	FRA	1.27	Shipments	JAP	-0.29
ISM Manufacturing	US	1.07	GDP Final	US	-0.28
Consumer Credit	UK	0.56	Tertiary Index	JAP	-0.20
Unemployment	GER	0.63	GDP Revised	EU	-0.50
Unemployment	EU	0.53	Halifax House Prices	UK	-0.25
Consumer Confidence	UK	0.51	PMI	EU	-0.27
Nationwide House Prices	UK	0.44	GDP Final	FRA	-0.24
Retail Sales	EU	0.54	Capital Account	GER	-0.26
Trade Balance	US	0.52	Existing Home Sales	US	-0.28
CIPS Manufacturing	UK	0.49	Construction Spending	US	-0.42
Chicago PMI	US	0.53	PPI	UK	-0.33
Dept. Store Sales	JAP	0.51	GDP	JAP	-0.90
Retail Sales	GER	0.37	Services Index	EU	-0.40
M2	JAP	0.38	PPI	FRA	-0.61
M2	US	0.23	Leading Indicators	US	-0.65
Consumer Credit	US	0.43	Employment	GER	-0.42
Coincident Index	JAP	0.49	Chicago Ntl. Activity Index	US	-0.51
Business Climate Index	EU	0.29	Trade Balance	JAP	-0.53
GDP Provisional	UK	0.69	IFO Manufacturing Survey	GER	-0.68
OECD Leading Indicators	EU	0.60	New Home Sales	US	-0.75
HCPI	UK	0.32	Tokyo Dept. Store Sales	JAP	-0.61
Household Survey	FRA	0.31	Industrial Production	GER	-0.48
Factory Inventories/Orders	US	0.34	Business Inventories	US	-0.84
Retail Sales	JAP	0.39	PSNCR	UK	-0.60
Import Prices	US	0.20	Income	JAP	-1.27
NAHB Housing Index	US	0.19	Current Account	FRA	-0.92
PPI	US	0.21	Treasury Budget	US	-1.26
Unemployment	FRA	0.29	CPI	JAP	-1.39
Manufacturing Orders	GER	0.18	Unemployment	JAP	-1.47
Current Account	EU	0.22	Construction Orders	JAP	-1.59
Productivity Preliminary	US	0.60	Challenger Layoffs	US	-0.96
Supermarket Sales	JAP	0.24	M4 Provisional	UK	-0.89
Labour Costs Final	EU	0.34	INSEE Report	FRA	-4.26
Current Account	GER	0.18	Tankan Manuf. Survey	JAP	-5.25
Trade Balance	GER	0.18	GDP Final	EU	-1.73
GDP Revised	JAP	0.24	Trade Balance	UK	-1.05
GDP Preliminary	UK	0.11	CPI	US	-1.74
Productivity Revised	US	0.14	FX Reserves	JAP	-1.85
Housing Completions	US	0.10			

Table A.2.5. Insignificant Announcement Effects for EUR-JPY Using FFF Model.

ANNOUNCEMENT	COUNTRY	COEFF	ANNOUNCEMENT	COUNTRY	COEFF
Retail Sales	US	0.77	Tertiary Index	JAP	0.03
Current Account	EU	0.79	OECD Leading Indicators	EU	0.02
Non-Farm Payrolls Prelim.	FRA	1.62	CPI	US	0.00
Labour Costs Final	EU	1.54	Industrial Production	GER	-0.03
M4 Provisional	UK	0.56	Unemployment	FRA	-0.17
Current Account	FRA	0.56	Retail Sales	JAP	-0.11
PSNCR	UK	0.48	CPI Final	FRA	-0.10
Import Prices	GER	0.56	Halifax House Prices	UK	-0.19
Consumer Confidence	JAP	0.51	Tankan Manuf. Survey	JAP	-1.11
Labour Costs Revised	EU	0.96	Unemployment	EU	-0.17
NAHB Housing Index	US	0.52	Construction Orders	JAP	-0.34
ISM Manufacturing	US	1.23	Shipments	JAP	-0.36
CPI Preliminary	FRA	0.57	IFO Manufacturing Survey	GER	-0.20
Business Climate	FRA	0.39	GDP Final	EU	-0.23
Retail Sales	EU	0.44	Personal Income	US	-0.65
Current Account	GER	0.71	GDP Revised	EU	-0.54
Trade Balance	GER	0.71	Leading Indicators	US	-0.72
GDP	GER	0.63	Services Index	GER	-0.39
CIPS Manufacturing	UK	0.37	M2	US	-0.28
Housing Completions	US	0.39	Productivity Revised	US	-0.52
Challenger Layoffs	US	0.39	GDP Revised	JAP	-0.83
Productivity Preliminary	US	0.61	Trade Balance	UK	-0.35
Manufacturing Orders	GER	0.27	Employment	GER	-0.53
PMI	FRA	0.32	Treasury Budget	US	-0.98
M3	EU	0.31	INSEE Report	FRA	-2.62
Consumer Confidence	EU	0.33	GDP Final	FRA	-0.58
ISM Non Manufacturing	US	0.28	Consumer Credit	UK	-0.62
Initial Claims	US	0.13	Industrial Production	JAP	-1.10
Consumer Credit	US	0.28	Unemployment	GER	-0.62
Services Index	EU	0.16	GDP Preliminary	FRA	-1.17
Business Climate Index	EU	0.24	Retail Sales	UK	-0.54
Dept. Store Sales	JAP	0.27	Capital Account	GER	-0.64
PMI	EU	0.23	HCPI	UK	-0.59
Construction Spending	US	0.28	Services Index	FRA	-0.72
COL Preliminary	GER	0.18	Income	JAP	-1.23
Industrial Production	US	0.19	M4 Final	UK	-0.83
PPI	UK	0.17	PPI	EU	-0.76
Consumer Confidence	UK	0.18	GDP Final	US	-1.42
Unemployment	UK	0.11	GDP Preliminary	EU	-1.37
Coincident Index	JAP	0.19	Unemployment	JAP	-1.40
MPC Interest Rate	UK	0.13	ZEW Expectations	GER	-0.64
PMI	GER	0.10	CIPS Services	UK	-0.97
GDP Advance	US	0.13	Supermarket Sales	JAP	-1.48
Household Survey	FRA	0.04	PPI	FRA	-1.81
GDP Preliminary	UK	0.04	CPI	JAP	-1.92

Table A.2.6. Insignificant Announcement Effects for EUR-JPY Using Spline Model.

ANNOUNCEMENT	COUNTRY	COEFF	ANNOUNCEMENT	COUNTRY	COEFF
Consumer Confidence	JAP	0.63	Construction Orders	JAP	-0.12
FX Reserves	JAP	0.71	GDP Final	EU	-0.06
Labour Costs Final	EU	1.32	Services Index	GER	-0.11
Non-Farm Payrolls Prelim.	FRA	1.34	IFO Manufacturing Survey	GER	-0.09
CIPS Manufacturing	UK	0.57	Industrial Production	GER	-0.10
Industrial Production	FRA	0.60	Tertiary Index	JAP	-0.19
Trade Balance	FRA	0.61	Household Survey	FRA	-0.21
NAHB Housing Index	US	0.52	Tankan Manuf. Survey	JAP	-1.31
Housing Completions	US	0.52	Unemployment	FRA	-0.40
Services Index	EU	0.40	Personal Income	US	-0.52
M3	EU	0.55	Employment	GER	-0.28
PMI	FRA	0.57	Retail Sales	JAP	-0.33
ISM Manufacturing	US	1.14	Productivity Revised	US	-0.35
Initial Claims	US	0.28	CPI Final	FRA	-0.30
Labour Costs Revised	EU	0.77	Shipments	JAP	-0.57
Productivity Preliminary	US	0.69	Unemployment	EU	-0.30
PMI	EU	0.48	Consumer Credit	UK	-0.34
Current Account	FRA	0.32	Retail Sales	UK	-0.29
Unemployment	UK	0.34	Halifax House Prices	UK	-0.41
PPI	UK	0.37	Leading Indicators	US	-0.71
Industrial Production	US	0.38	Unemployment	GER	-0.36
Challenger Layoffs	US	0.34	HCPI	UK	-0.35
CPI Preliminary	FRA	0.33	GDP Revised	EU	-0.66
PMI	GER	0.35	Services Index	FRA	-0.45
Consumer Credit	US	0.34	Treasury Budget	US	-0.89
Retail Sales	EU	0.26	M4 Final	UK	-0.55
Current Account	GER	0.42	GDP Final	FRA	-0.56
Trade Balance	GER	0.42	INSEE Report	FRA	-2.51
Import Prices	GER	0.22	Capital Account	GER	-0.50
ISM Non Manufacturing	US	0.28	GDP Revised	JAP	-1.05
GDP	GER	0.32	Trade Balance	UK	-0.46
Manufacturing Orders	GER	0.20	ZEW Expectations	GER	-0.47
Dept. Store Sales	JAP	0.29	Industrial Production	JAP	-1.18
Construction Spending	US	0.33	CIPS Services	UK	-0.69
Business Climate	FRA	0.15	GDP Final	US	-1.28
Coincident Index	JAP	0.35	Income	JAP	-1.21
GDP Preliminary	UK	0.26	Supermarket Sales	JAP	-1.24
Consumer Confidence	EU	0.16	GDP Preliminary	FRA	-1.37
GDP Advance	US	0.26	Unemployment	JAP	-1.37
COL Preliminary	GER	0.13	GDP Preliminary	EU	-1.43
CPI	US	0.14	M2	US	-0.59
Consumer Confidence	UK	0.10	PPI	EU	-0.90
Business Climate Index	EU	0.08	PPI	FRA	-1.97
MPC Interest Rate	UK	0.02	CPI	JAP	-1.87
OECD Leading Indicators	EU	-0.09			

BIBLIOGRAPHY

Admati, A. R. and Pfleiderer, P. (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial Studies* 1, 3-40.

Aït-Sahalia, Y. (2002). Telling from discrete data whether the underlying continuous-time model is a diffusion. *Journal of Finance* 57, 2075-2112.

Aït-Sahalia, Y. (2004). Disentangling diffusion from jumps. *Journal of Financial Economics* 74, 487-528.

Aït-Sahalia, Y., Mykland, P. A. and Zhang, L. (2005). How often to sample a continuous time process in the presence of market microstructure noise. *Review of Financial Studies* 18, 351-416.

Almeida, A., Goodhart, C. and Payne, R. (1998). The effects of macroeconomic news on high frequency exchange rate behaviour. *Journal of Financial and Quantitative Analysis* 33, 383-408.

Amato, J. D. and Swanson, N. R. (2001). The real-time predictive content of money for output. *Journal of Monetary Economics* 48, 3-24.

Andersen, T. G., Benzoni, L. and Lund, J. (2002). An empirical investigation of continuous-time equity return models. *Journal of Finance* 57, 1239-1284.

Andersen, T. G. and Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance* 4, 115-158.

Andersen, T. G. and Bollerslev, T. (1997a). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance* 4, 115-158.

Andersen, T. G. and Bollerslev, T. (1997b). Heterogeneous information arrivals and return volatility dynamics: Uncovering the long-run in high frequency returns. *Journal of Finance* 52, 975-1005.

Andersen, T. G. and Bollerslev, T. (1998a). Deutsche mark-dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. *Journal of Finance* 53, 219-265.

Andersen, T. G. and Bollerslev, T. (1998b). Answering the sceptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review* 39, 885-905.

Andersen, T. G., Bollerslev, T. and Cai, J. (2000). Intraday and interday volatility in the Japanese stock market. *Journal of International Financial Markets, Institutions and Money* 10, 107-130.

Andersen, T. G., Bollerslev, T. and Das, A. (1998). Testing for market microstructure effects in intraday volatility: A reassessment of the Tokyo FX experiment. NBER Working Paper 6666.

Andersen, T. G., Bollerslev, T. and Diebold, F. X. (2007a). Parametric and nonparametric measurements of volatility. In Handbook of Financial Econometrics (eds. Y. Aït-Sahalia and L. P. Hansen), Amsterdam: North-Holland, forthcoming.

Andersen, T. G., Bollerslev, T. and Diebold, F. X. (2007b). Roughing it up: Including jump components in the measurement and forecasting of return volatility. *Review of Economics and Statistics*, forthcoming.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Ebens, H. (2001). The distribution of realised stock return volatility. *Journal of Financial Economics* 61, 43-76.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2000a). Exchange rate returns standardised by realised volatility are (nearly) Gaussian. *Multinational Finance Journal* 4, 159-179.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2000b). Great realisations. *Risk* 13, 105-108.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2001a). Exchange rate returns standardised by realised volatility are (nearly) Gaussian. *Multinational Finance Journal* 4, 159-179.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2001b). The distribution of realised exchange rate volatility. *Journal of the American Statistical Association* 96, 42-55.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2003). Modelling and forecasting realised volatility. *Econometrica* 71, 579-625.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Vega, C. (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review* 93, 38-62.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Vega, C. (2007). Real-time price discovery in stock, bond and foreign exchange markets. *Journal of International Economics*, forthcoming.

Andersen, T. G., Bollerslev, T. and Dobrev, D. (2007). No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. *Journal of Econometrics* 138, 125-180.

Andersen, T. G., Bollerslev, T., Frederiksen, P. H. and Nielsen, M. Ø. (2006). Continuous-time models, realized volatilities, and testable distributional implications for daily stock returns. Manuscript, Duke University.

Andersen, T. G., Bollerslev, T. and Lange, S. (1999). Forecasting financial market volatility: Sample frequency vis-à-vis forecast horizon. *Journal of Empirical Finance* 6, 457-477.

Andersen, T. G., Bollerslev, T. and Meddahi, N. (2004). Analytic evaluation of volatility forecasts. *International Economic Review* 45, 1079-1110.

Andersen, T. G., Bollerslev, T. and Meddahi, N. (2005). Correcting the errors: Volatility forecast evaluation using high-frequency data and realised volatilities. *Econometrica* 73, 279-296.

Andersen, T. G. and Lund, J. (1997). Estimating continuous-time stochastic volatility models of the short-term interest rate. *Journal of Econometrics* 77, 343-377.

Andreou, E. and Ghysels, E. (2002). Detecting multiple breaks in financial market volatility dynamics. *Journal of Applied Econometrics* 17, 579-600.

ap Gwilym, O., McMillan, D. G. and Speight, A. E. H. (1999). The intraday relationship between volume and volatility in LIFFE futures markets. *Applied Financial Economics* 9, 593-604.

Aradhyula, S. V. and Ergün, A. T. (2004). Trading collar, intraday periodicity and stock market volatility. *Applied Financial Economics* 14, 909-913.

Areal, N. M. P. C., and Taylor, S. J. (2002). The realized volatility of FTSE-100 futures prices. *Journal of Futures Markets* 22, 627-648.

Baillie, R. T. (1996). Long memory processes and fractional integration in econometrics. *Journal of Econometrics* 73, 5-59.

Baillie, R. T. and Bollerslev, T. (1990). Intraday and inter-market volatility in foreign exchange rates. *Review of Economic Studies* 58, 565-585.

Baillie, R. T., Bollerslev, T. and Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 74, 3-30.

Bakshi, G., Cao, C. and Chen, Z. (1997). Empirical performance of alternative option pricing models. *Journal of Finance* 52, 2003-2049.

Balduzzi, P., Elton, E. J. and Green, T. C. (2001). Economic news and bond prices: Evidence from the U.S. treasury market. *Journal of Financial and Quantitative Analysis* 36, 523-543.

Ball, R. (1978). Anomalies in relationships between securities' yields and yield-surrogates. *Journal of Financial Economics* 6, 103-126.

Ballocchi, G., Dacorogna, M. M., Hopman, C. M., Müller, U. A. and Olsen, R. B. (1999). The intraday multivariate structure of the Eurofutures markets. *Journal of Empirical Finance* 6, 479-513.

Bandi, F. M. and Nguyen, T. H. (2003). On the functional estimation of jump-diffusion models. *Journal of Econometrics* 116, 293-328.

Bandi, F. M. and Russell, J. R. (2005). Microstructure noise, realized volatility, and optimal sampling. Manscript, University of Chicago.

Bandi, F. M. and Russell, J. R. (2006). Separating microstructure noise from volatility. *Journal of Financial Economics* 79, 655-692.

Banz, R.W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics* 9, 3-18.

Barndorff-Nielsen, O. E. and Shephard, N. (1998). Continuous time volatility: Model construction and inference. Department of Mathematical Sciences, University of Aarhus and Nuffield College, Oxford.

Barndorff-Nielsen, O.E. and Shephard, N. (2001). Non-Gaussian Ornstein-Uhlenbeck-based models and some of their uses in financial economics. *Journal of the Royal Statistics Society, B*, 63, 167-241.

Barndorff-Nielsen, O.E. and Shephard, N. (2002a). Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistics Society, B*, 64, 253-280.

Barndorff-Nielsen, O.E. and Shephard, N. (2002b). Estimating quadratic variation using realized variance. *Journal of Applied Econometrics* 17, 457-477.

Barndorff-Nielsen, O.E. and Shephard, N. (2003). Realized power variation and stochastic volatility. *Bernoulli* 9, 243-265.

Barndorff-Nielsen, O.E. and Shephard, N. (2004a). How accurate is the asymptotic approximation to the distribution of realised variance? In *Identification and Inference for Economic Models. A Festschrift in Honour of T. J. Rothenberg* (eds. D. W. F Andrews, J. L. Powell, P. A. Ruud and J. H. Stock), Cambridge, UK: Cambridge University Press.

Barndorff-Nielsen, O.E. and Shephard, N. (2004b). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics* 2, 1-37.

Barndorff-Nielsen, O.E. and Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics* 4, 1-30.

Barucci, E. and Reno, R. (2002). On measuring volatility and the GARCH forecasting performance. *Journal of International Financial Markets* 12, 183-200.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *Journal of Finance* 32, 663-682.

Bates, D. S. (1996). Jumps and stochastic volatility: Exchange rate processes implicit in Deutsche Mark options. *Review of Financial Studies* 9, 69-107.

Bates, D. S. (2000). Post-'87 crash fears in the S&P 500 futures option market. *Journal of Econometrics* 94, 181-238.

Bauwens, L., Omrane, W. B. and Giot, P. (2005). News announcements, market activity and volatility in the euro/dollar foreign exchange market. *Journal of International, Money and Finance* 24, 1108-1125.

Becker, K. G., Finnerty, J. E. and Kopecky, K. J. (1993). Economic news and intraday volatility in international bond markets. *Financial Analysts Journal* 49, 81-86.

Bera, A. K. and Higgins, M. L. (1993). ARCH models: properties, estimation and testing. *Journal of Economic Surveys* 7, 305-362.

Berkowitz, J. and Giorgianni, L. (2001). Long-horizon exchange rate predictability? *Review of Economics and Statistics* 83, 81-91.

Black, F., Jensen, M. C. and Scholes, M. (1972). The capital asset pricing model: Some empirical tests. In Studies in the Theory of Capital Markets (ed. M. C. Jensen), Praeger, New York, NY, USA.

Blake, N., Henry, S. G. B. and Robertson, D. (2002). Term structure forecasts of inflation: Some further results. *The Manchester School* 70, 822-832.

Blume, M. E. and Friend, I. (1973). A new look at the capital asset pricing model. *Journal of Finance* 28, 19-33.

Bodie, Z. (1976). Common stocks as a hedge against inflation. *Journal of Finance* 31, 459-470.

Bollen, B. and Inder. B. (2002). Estimating daily volatility in financial markets utilizing intraday data. *Journal of Empirical Finance* 9, 551-562.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307-327.

Bollerslev, T. and Domowitz, I. (1993). Trading patterns and prices in the interbank foreign exchange market. *Journal of Finance* 48, 1421-1443.

Bollerslev, T. and Mikkelsen, H. O. (1996). Modelling and pricing long memory in stock market volatility. *Journal of Econometrics* 73, 151-184.

Bollerslev, T. and Wright, J. H. (2000). Semiparametric estimation of long-memory volatility dependencies: The role of high-frequency data. *Journal of Econometrics* 98, 81-106.

Bollerslev, T. and Wright, J.H. (2001). Volatility forecasting, high frequency data and frequency domain inference. *Review of Economics and Statistics* 83, 596-602.

Bollerslev, T. and Zhou, H. (2002). Estimating stochastic volatility diffusion using conditional moments of integrated volatility. *Journal of Econometrics* 109, 33-65.

Bollerslev, T., Cai, J. and Song, F. M. (2000). Intraday periodicity, long memory volatility, and macroeconomic announcement effects in the US Treasury bond market. *Journal of Empirical Finance* 7, 37-55.

Bollerslev, T., Chou, R. Y. and Kroner, K. F. (1992). ARCH modeling in finance. *Journal of Econometrics* 52, 5-59.

Bollerslev, T., Engle, R. F. and Nelson, D. B. (1994). ARCH models. In Handbook of Econometrics, vol.4 (eds. R. F. Engle and D. McFadden), Elsevier Science B.V., Amsterdam.

Bollerslev, T., Kretschmer, U., Pigorsch, C. and Tauchen G. (2005). A discrete-time model for daily S&P500 returns and realized variations: Jumps and leverage effects. Manuscript, Duke University.

Bollerslev, T., Litvinova, J. and Tauchen, G. (2006). Leverage and volatility feedback effects in high frequency data. *Journal of Financial Econometrics* 4, 353-384.

Boyd, J. H., Jagannathan, R. and Hu, J. (2001). The stock market's reaction to unemployment news: Why bad news is usually good news for stocks. NBER Working Paper No. w8092.

Brock, W.A. and Kleidon, A.W. (1992). Periodic market closure and trading volume. *Journal of Economic Dynamics and Control* 16, 451-489.

Cai, C. X., Hudson, R. and Keasey, K. (2004). Intraday bid-ask spreads, trading volume and volatility: Recent empirical evidence from the London Stock Exchange. *Journal of Business, Finance and Accounting* 31, 647-676.

Campbell, J. Y. (1987). Stock returns and the term structure. *Journal of Financial Economics* 18, 373-399.

Castanias, II, R. P. (1979). Macroinformation and the variability of stock market prices. *Journal of Finance* 34, 439-450.

Chan, K. C., Chen, N.-F. and Hsieh, D. A. (1985). An exploratory investigation of the firm size effect. *Journal of Financial Economics* 14, 451-471.

Chan, L. K. C., Karceski, J. and Lakonishok, J. (1998). The risk and return from factors. *Journal of Financial and Quantitative Analysis* 33, 159-188.

Chang, Y. and Taylor, S. J. (2003). Information arrivals and intraday exchange rate volatility. *International Financial Markets, Institutions and Money* 13, 85-112.

Chen, N.-F. (1983). Some empirical tests of the theory of arbitrage pricing. *Journal of Finance* 38, 1393-1414.

Chen, N.-F. (1991). Financial investment opportunities and the macroeconomy. *Journal of Finance* 46, 529-554.

Chen, N.-F., Roll, R. and Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business* 59, 383-403.

Chernov, M. Gallant, R. A., Ghysels, E. and Tauchen, G. (2003). Alternative models for stock price dynamics. *Journal of Econometrics* 116, 225-257.

Cho, D. C., Elton, E. J. and Gruber, M. J. (1984). On the robustness of the Roll and Ross arbitrage pricing theory. *Journal of Financial and Quantitative Analysis* 19, 1-10.

Christoffersen, P., Ghysels, E. and Swanson, N. R. (2002). Let's get "real" about using economic data. *Journal of Empirical Finance* 9, 343-360.

Clark, P. K. (1973). A subordinated stochastic process model with finite variance for speculative prices. *Econometrica* 41, 135-155.

Cole, R. (1969). Data errors and forecasting accuracy. In Economic Forecasts and Expectations: Analyses of Forecasting Behaviour and Performance (ed. J. Mincer), National Bureau of Economic Research, Columbia University Press, NY, USA.

Comte, F. and Renault, E. (1998). Long memory in continuous time stochastic volatility models. *Mathematical Finance* 8, 291-323.

Connor, G. (1984). A unified beta pricing theory. *Journal of Economic Theory* 34, 13-31.

Connor, G. and Korajczyk, R. A. (1988). Risk and return in equilibrium APT: Application of a new test methodology. *Journal of Financial Economics* 21, 255-289.

Copeland, T. E. (1976). A model of asset trading under the assumption of sequential information arrival. *Journal of Finance* 31, 1149-1168.

Corsi, F., Zumbach, G., Müller, U. A. and Dacorogna, M. (2001). Consistent high-precision volatility from high frequency data. *Economic Notes* 30, 183-204.

Cox, J. C, Ingersoll, J. E. and Ross, S. A. (1985). A theory of the term structure of interest rates. *Econometrica* 53, 385-407.

Croushore, D. and Stark, T. (2001). A real-time data set for macroeconomists. *Journal of Econometrics* 105, 111-130.

Cumby, R., Figlewski, S. and Harsbrouck, J. (1993). Forecasting volatility and correlations with EGARCH models. *Journal of Derivatives*, winter 93, 51-63.

Cyree, K. B., Griffiths, M. D. and Winters, D. B. (2004). An empirical examination of the intraday volatility in euro-dollar rates. *The Quarterly Review of Economics and Finance* 44, 44-57.

Dacorogna, M. M., Müller, U. A., Nagler, R. J., Olsen, R. B. and Pictet, O. V. (1993). A geographical model for the daily and weekly seasonal volatility in the foreign exchange market. *Journal of International Money and Finance* 12, 413-438.

Dacorogna, M. M., Müller, U. A., Olsen, R. B. and Pictet, O. V. (1997). Modelling short term volatility with GARH and HARCH models. Olsen and Associates Research Group, Zurich.

Daigler, R. T. (1997). Intraday futures volatility and theories of market behaviour. *Journal of Futures Markets* 17, 45-74.

Das, S. R. (2002). The surprise element: Jumps in interest rates. *Journal of Econometrics* 106, 27-65.

De Bondt, W. F. M. and Thaler, R. (1985). Does the stock market overreact? *Journal of Finance* 40, 793-805.

De Bondt, W. F. M. and Thaler, R. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance* 42, 557-581.

DeGennaro, R. P. and Shrieves, R. E. (1997). Public information releases, private information arrival and volatility in the foreign exchange market. *Journal of Empirical Finance* 4, 295-315.

Dempster, A. P., Laird, N. M. and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistics Society*, Series B, 39, 1-38.

Dhrymes, P. J., Friend, I. and Gultekin, N. B. (1984). A critical reexamination of the empirical evidence on the arbitrage pricing theory. *Journal of Finance* 39, 323-346.

Dhrymes, P. J., Friend, I., Gultekin, M. N. and Gultekin, N. B. (1985). New tests of the APT and their implications. *Journal of Finance* 40, 659-674.

Diebold, F. X. and Rudebusch, G. D. (1991). Forecasting output with a composite leading index: A real-time analysis. *Journal of the American Statistical Association* 86, 603-610.

Ding, Z. X. and Granger, C. W. J. (1996). Modeling volatility properties of speculative returns: a new approach. *Journal of Econometrics* 73, 185-215.

Ding, Z. X., Granger, C. W. J. and Engle, R. F. (1993). Long memory properties of stock market returns and a new model. *Journal of Empirical Finance* 1, 83-106.

Docking, D. S., Kawaller, I. G. and Koch, P. D. (1999). Midday volatility spikes in U.S. futures markets. *Journal of Futures Markets* 19, 195-216.

Drost, F. C. and Nijman, T. E. (1993). Temporal aggregation of GARCH processes. *Econometrica* 61, 909-927.

Drost, F. C. and Werker, B. J. M. (1996). Closing the GARCH gap: Continuous time GARCH modelling. *Journal of Econometrics* 74, 31-57.

Duffie, D, Pan, J. and Singleton, K. (2000). Transform analysis and asset pricing for affine jump-diffusions. *Econometrica* 68, 1343-1376.

Dybvig, P. H. (1983). An explicit bound on individual assets' deviations from APT pricing in a finite economy. *Journal of Financial Economics* 12, 483-496.

Dybvig, P. H. and Ross, S. A. (1985). Yes, the APT is testable. *Journal of Finance* 40, 1173-1188.

Ederington, L. H. and Lee, J. H. (1993). How markets process information: News releases and volatility. *Journal of Finance* 48, 1161-1191.

Ederington, L. H. and Lee, J. H. (1995). The short-run dynamics of the price adjustment to new information. *Journal of Financial and Quantitative Analysis* 30, 117-134.

Eggington, D. M., Pick, A. and Vahey, S. P. (2002). 'Keep it real!': A real-time UK macro data set. *Economic Letters* 77, 15-20.

Ehrmann M. and Fratzscher, M. (2005). Exchange rates and fundamentals: New evidence from real-time data. *Journal of International Money and Finance* 24, 317-341.

Ekman, P. D. (1992). Intraday patterns in the S&P 500 index futures market. *Journal of Futures Markets* 12, 365-381.

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50, 987-1007.

Epps, T. W. and Epps, M. L. (1976). The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis. *Econometrica* 44, 305-321.

Eraker, B. (2001). MCMC analysis of diffusion models with application to finance. *Journal of Business and Economic Statistics* 19, 177-191.

Eraker, B. (2004). Do stock prices and volatility jump? Reconciling evidence from spot and option prices. *Journal of Finance* 59, 1367-1403.

Eraker, B., Johannes, M. and Polson, N. (2003). The impact of jumps in volatility and returns. *Journal of Finance* 58, 1269-1300.

Evans, M. D. D. and Lyons, R. K. (2002). Order flow and exchange rate dynamics. *Journal of Political Economy* 110, 170-180.

Evans, M. D. D. and Lyons, R. K. (2005). Do currency markets absorb news quickly? *Journal of International Money and Finance* 24, 197-217.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance* 25, 383-417.

Fama, E. F. (1981). Stock returns, real activity, inflation and money. *American Economic Review* 71, 545-565.

Fama, E. F. (1990). Stock returns, expected returns and real activity. *Journal of Finance* 45, 1089-1108.

Fama, E. F. (1991). Efficient capital markets: II. *Journal of Finance* 46, 1575-1617.

Fama, E. F. and French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25, 23-49.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance* 47, 427-465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.

Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51, 55-84.

Fama, E. F. and Gibbons, M. R. (1984). A comparison of inflation forecasts. *Journal of Monetary Economics* 13, 327-348.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81, 607-636.

Fama, E. F. and Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics* 5, 115-146.

Faust, J., Rogers, J. H. and Wright, J. (2003). Exchange rate forecasting: The errors we've really made. *Journal of International Economics* 60 35-59.

Ferson, W. E. and Harvey, C. R. (1991). The variation of economic risk premiums. *Journal of Political Economy* 99, 385-415.

Figlewski, S. (1997). Forecasting volatility. *Financial Markets, Institutions and Instruments* 6, 1-88.

Flannery, M. J. and Protopapadakis, A. A. (2002). Macroeconomic factors do influence aggregate stock returns. *Review of Financial Studies* 15, 751-782.

Fleming, M. J. and Remolona, E. M. (1999). Price formation and liquidity in the US treasury market: The response to public information. *Journal of Finance* 54, 1901-1915.

Franses, P. H. and van Dijk, D. (1996). Forecasting stock market volatility using (non-linear) GARCH models. *Journal of Forecasting* 15, 229-235.

Franses, P. H., van der Leij, M. and Paap, R. (2002). Modelling and forecasting level shifts in absolute returns. *Journal of Applied Econometrics* 17, 601-616.

French, K. R., Schwert, G. W. and Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics* 19, 3-29.

Galati, G. and Ho, C. (2003). Macroeconomic news and the euro/dollar exchange rate. *Economic Notes by Banca Monte dei Paschi di Siena SpA* 32, 371-398.

Gallant, A. R. and Tauchen, G. E. (1996). Which moment to match? *Econometric Theory* 12, 657-681.

Gençay, R., Selçuk, F. and Whitcher, B. (2001). Differentiating intraday seasonalities through wavelet multi-scaling. *Physica A* 289, 543-556.

Geweke, J. and Porter-Hudak, S. (1983). The estimation and application of long memory time series models. *Journal of Time Series Analysis* 4, 221-238.

Goodhart, C. A. E., Hall, S. G., Henry, S. G. B. and Pesaran, B. (1993). News effects in a high frequency model of the sterling-dollar exchange rate. *Journal of Applied Econometrics* 8, 1-13.

Granger, C. W. J. and Ding, Z. X. (1996). Varieties of long memory models. *Journal of Econometrics* 73, 61-77.

Granger, C. W. J. and Hyung, N. (2004). Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. *Journal of Empirical Finance* 11, 399-421.

Granger, C. W. J. and Joyeux, R. (1980). An introduction to long-memory time series models and fractional differencing. *Journal of Time Series Analysis* 1, 15-29.

Green, T. C. (2004). Economic news and the impact of trading on bond prices. *Journal of Finance* 59, 1201-1233

Grinblatt, M. and Titman, S. (1983). Factor pricing in a finite economy. *Journal of Financial Economics* 12, 497-507.

Guillaume, D. M., Pictet, O. V. and Dacorogna, M. M. (1995). On the intradaily performance of GARCH processes. Olsen and Associates Research Group, Zurich.

Hamao, Y. (1988). An empirical examination of the arbitrage pricing theory. *Japan and the World Economy* 1, 45-61.

Hansen, P. R. and Lunde, A. (2006a). Consistent ranking of volatility models. *Journal of Econometrics* 131, 97-121.

Hansen, P. R. and Lunde, A. (2006b). Realized variance and market microstructure noise. *Journal of Business and Economic Statistics* 24, 127-161.

Hardouvelis, G.A. (1988). Economic news, exchange rates and interest rates. *Journal of International Money and Finance* 7, 23-35.

Harris, L. (1986). A transactions data study of weekly and intradaily patterns in stock returns. *Journal of Financial Economics* 16, 99-117.

Harvey, C. R. and Huang, R. D. (1991). Volatility in the foreign currency futures market. *Review of Financial Studies* 4, 543-569.

Harvey, A. C. and Shephard, N. (1994). Estimation of an asymmetric stochastic volatility model for asset returns. *Journal of Business and Economic Statistics* 14, 429-434

Hasbrouck, J., (2003). Intraday price formation in US equity index markets. *Journal of Finance* 58, 2375-2400.

Hawawini, G. and Keim, D. B. (1997). The cross-section of common stock returns: A review of the evidence and some new findings. INSEAD Working Paper No. 97/66/FIN.

Heston, S. L. (1993). A closed for solution for options with stochastic volatility, with applications to bond and currency options. *Review of Financial Studies* 6, 327-343.

Hosking, J. R. M. (1981). Fractional differencing. *Biometrika* 68, 165-176.

Howrey, E. P. (1978). The use of preliminary data in econometric forecasting. *Review of Economics and Statistics* 60, 193-200.

Hsieh, D. A. (1991). Chaos and non-linear dynamics: Application to financial markets. *Journal of Finance* 46, 1839-1877.

Huang, X. and Tauchen, G. (2005). The relative contribution of jumps to total price variation. *Journal of Financial Econometrics* 3, 456-499.

Hull, J. C. and White, A. (1987). The pricing of options on assets with stochastic volatilities. *Journal of Finance* 42, 281-300.

Ito, T., Lyons, R. K. and Melvin, M. T. (1998). Is there private information in the FX market? The Tokyo experiment. *Journal of Finance* 53, 1111-1130.

Jacquier, E., Polson, N. G. and Rossi, P. E. (1994). Bayesian analysis of stochastic volatility models. *Journal of Business and Economic Statistics* 12, 371-389.

Janses, D.-J. and De Haan, J. (2005). Talking heads: The effects of ECB statements on the euro-dollar exchange rate. *Journal of International Money and Finance* 24, 343-361.

Jarque, C. M. and Bera, A. K. (1987). Test for normality of observations and regressions residuals. *International and Statistical Review*, 55, 163-172.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48, 65-91.

Jennings, R. H., Starks, L. T. and Fellingham, J. C. (1981). An equilibrium model of asset trading with sequential information arrival. *Journal of Finance* 36, 143-161.

Johannes, M. (2004). The statistical and economic role of jumps in continuous-time interest rate models. *Journal of Finance* 59, 227-260.

Jones, C. M., Kaul, G. and Lipson, M. L. (1994). Information, trading and volatility. *Journal of Financial Economics* 36, 127-154.

Jones, C. M., Lamont, O. and Lumsdaine, R. L. (1998). Macroeconomic news and bond market volatility. *Journal of Financial Economics* 47, 315-337.

Jorion, P. (1988). On jump processes in the foreign exchange and stock markets. *Review of Financial Studies* 1, 427-445.

Jorion, P. (1995). Predicting volatility in the foreign exchange market. *Journal of Finance* 50, 507-528.

Jorion, P. (1996). Risk and turnover in the foreign exchange market. In The Microstructure of Foreign Exchange Markets (eds. J. A. Franke, G. Galli and A. Giovannini), Chicago: Chicago University Press.

Kawaller, I. G., Koch, P. D. and Koch, T. W. (1990). Intraday relationships between volatility in S&P 500 futures prices and volatility in the S&P 500 index. *Journal of Banking and Finance* 14 373-397.

Kawaller, I. G., Koch, P. D. and Peterson, J. E. (1994). Assessing the intraday relationship between implied and historical volatility. *Journal of Futures Markets* 14, 323-346.

Khil, J. and Lee, B.-S. (2000). Are common stocks a good hedge against inflation? Evidence from the Pacific-rim countries. *Pacific-Basin Finance Journal* 8, 457-482.

Lamont, O. A. (2001). Economic tracking portfolios. *Journal of Econometrics* 105, 161-184.

Lee, J. H. and Linn, S. C. (1994). Intraday and overnight volatility of stock index and stock index futures returns. *Review of Futures Markets* 13, 1-30.

Lehman, B. N. and Modest, D. M. (1988). The empirical foundations of the arbitrage pricing theory. *Journal of Financial Economics* 21, 213-254.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics* 47, 13-37.

Litzenberger, R. H. and Ramaswamy, K. (1979). The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. *Journal of Financial Economics* 7, 163-195.

Ljung, G. M. and Box, G. E. P. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65, 297-303.

Lockwood, L. J. and Linn, S. C. (1990). An examination of stock market return volatility during overnight and intraday periods, 1964-1989. *Journal of Finance* 45, 591-601.

Love, R. and Payne, R., 2007. Macroeconomic news, order flow and exchange rates. *Journal of Financial and Quantitiative Analysis*, forthcoming.

Maheu, J. M. and McCurdy, T. H. (2004). News arrival, jump dynamics, and volatility components in individual stock returns. *Journal of Finance* 59, 755-793.

Mankiw, N. G., Runkle, D. E. and Shapiro, M. D. (1984). Are preliminary announcements of the money stock rational forecasts? *Journal of Monetary Economics* 14, 15-27.

Maravall, A. and Pierce, D. A. (1986). The transmission of data noise into policy noise in US monetary control. *Econometrica* 54, 961-979.

Mark, N. C. (1995). Exchange rates and fundamentals: Evidence on long-horizon predictability. *American Economic Review* 85, 201-218.

Mark, N. C. and Sul, D. (2001). Nominal exchange rates and monetary fundamentals: evidence form a small post-Bretton Woods panel. *Journal of International Economics* 53, 29-52.

Martens, M. (2001). Forecasting daily exchange rate volatility using intraday returns. *Journal of International Money and Finance* 20, 1-23.

Martens, M. (2002). Measuring and forecasting S&P500 index futures volatility using high frequency data. *Journal of Futures Markets* 22, 497-518.

Martinez, M. A. and Rubio, G. (1989). Arbitrage pricing with macroeconomic variables: An empirical investigation using Spanish data. Working Paper, Universidad del Pais Vasco.

McInish, T. H. and Wood, R. A. (1990). A transactions data analysis of the variability of common stock returns during 1980-1984. *Journal of Banking and Finance* 14, 99-112.

McMillan, D. G. and Speight, A. E. H. (2004). Forecasting exchange rate volatility: Daily forecasts and intra-day volatility appraisal. *Journal of Forecasting* 23, 449-460.

McMillan, D. G. and Speight, A. E. H. (2006). Non-linear dynamics and competing behavioural interpretations: Evidence from intra-day FTSE-100 index and futures data. *Journal of Futures Markets* 26, 343-368.

McMillan, D. G. and Speight, A. E. H. (2007). Heterogeneous components in high-frequency exchange rate volatility. *Finance Letters*, forthcoming

McQueen, G. and Roley, V. V. (1993). Stock prices, news, and business conditions. *Review of Financial Studies* 6, 683-707.

Meddahi, N. (2002). A theoretical comparison between integrated and realised volatility. *Journal of Applied Econometrics* 17, 475-508.

Meddahi, N. (2003). ARMA representation of integrated and realised variances. *The Econometrics Journal* 6, 334-355.

Meese, R. A. and Rogoff, K. (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics* 14, 3-24.

Merton, R. C. (1971). Optimum consumption and portfolio rules in a continuous-time model. *Journal of Economic Theory* 3, 373-413.

Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics* 3, 125-144.

Miller, M. and Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *Journal of Business*, 34, 411-433.

Morana, C. and Beltratti, A. (2004). Structural change and long-range dependence in volatility of exchange rates: Either, neither or both? *Journal of Empirical Finance* 11, 629-658.

Morgenstern, O. (1963). On the Accuracy of Economic Observations, 2nd edn., Princeton University Press, Princeton, NJ, USA.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica* 34, 768-783.

Müller, U. A., Dacorogna, M. M., Dave, R. D., Olsen, R. B., Pictet, O. V. and von Weizsacker, J. E. (1997). Volatilities of different time resolutions – analyzing the dynamics of market components. *Journal of Empirical Finance* 4, 213-239.

Müller, U. A., Dacorogna, M. M., Olsen, R. B., Pictet, O. V., Schwarz, M. and Morgenegg, C. (1990). Statistical study of foreign exchange rates, empirical evidence of a price change scaling law, and intraday analysis. *Journal of Banking and Finance* 14, 1189-1208.

Nefti, S. N. (2007). Why financial markets do not use econometric forecasting: Foreign exchange exotics, central banks and position taking. *The Manchester School* Supplement 2007, 1-20.

Nelson, D. B. (1990a). Stationarity and persistence in the GARCH (1,1) model. *Econometric Theory* 6, 318-334.

Nelson, D. B. (1990b). ARCH models as diffusion approximations. *Journal of Econometrics* 45, 7-38.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica* 59, 347-370.

Nelson, D. B. (1992). Filtering and forecasting with misspecified ARCH models 1: Getting the right variance with the wrong model. *Journal of Econometrics* 52, 61-90.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703-8.

Oomen, R. C. A. (2005). Properties of biased-corrected realized variance under alternative sampling schemes. *Journal of Financial Econometrics* 4, 555-577.

Pan, J. (2002). The jump-risk premia implicit in options: Evidence from an integrated time-series study. *Journal of Financial Economics* 63, 3-50.

Patterson, K. D. and Heravi, S. M. (1991). Data revisions and the expenditure components of GDP. *The Economic Journal* 101, 887-901.

Payne, R. (1996). Announcement effects and seasonality in the intraday foreign exchange market. Discussion Paper 238, Financial Markets Group, London School of Economics.

Pearce, D. K. and Roley, V. V. (1985). Stock prices and economic news. *Journal of Business* 58, 49-67.

Perez, S. J. (2000). Revised or real time data: What should be used to characterise the FOMC's information set? Washington State University manuscript.

Poon, S. and Taylor, S. J. (1991). Macroeconomic factors and the UK stock market. *Journal of Business, Finance and Accounting* 18, 619-636.

Poterba, J. and Summers, L. (1986). The persistence of volatility and stock market fluctuations. *American Economic Review* 76, 1124-1141.

Prast, H. M. and de Vor, M. P. H. (2005). Investor reactions to news: A cognitive dissonance analysis of the euro-dollar exchange rate. *European Journal of Political Economy* 21, 115-141.

Reinganum, M. R. (1981). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yield and market values. *Journal of Financial Economics* 9, 19-46.

Reisen, V. A. (1994). Estimation of the fractional difference parameter in the ARFIMA (p,d,q) model using the smoothed periodogram. *Journal of Time Series Analysis* 15, 335-351.

Roll, R. (1977). A critique of the asset pricing theory's tests part I: On past and potential testability of the theory. *Journal of Financial Economics* 4, 129-176.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39, 1127-1139.

Roll, R. and Ross, S. A. (1980). An empirical investigation of the arbitrage pricing theory. *Journal of Finance* 35, 1073-1103.

Roll, R. and Ross, S. A. (1984). A critical re-examination of the empirical evidence on the arbitrage pricing theory: A reply. *Journal of Finance* 39, 347-350.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13, 341-360.

Ruiz, E. (1994). Quasi-maximum likelihood estimation of stochastic volatility models. *Journal of Econometrics* 63, 289-306.

Runkle, D. E. (1998). Revisionist history: How data revisions distort economic policy research. Federal Reserve Bank of Minneapolis Quarterly Review 22, 3-12.

Sager, M. J. and Taylor, M. P. (2004). The impact of European Central Bank Governing Council announcements on the foreign exchange market: A microstructural analysis. *Journal of International Money and Finance* 23, 1043-1051.

Schwert, G. W. (1981). The adjustment of stock prices to information about inflation. *Journal of Finance* 36, 15-29.

Schwert, G. W. (1989). Why does stock market volatility change over time? *Journal of Finance* 44, 1115-1153.

Schwert, G. W. (1990a). Stock returns and real activity: A century of evidence. *Journal of Finance* 45, 1237-1257.

Schwert, G. W. (1990b). Stock volatility and the crash of '87. *Review of Financial Studies* 3, 77-102.

Shanken, J. (1982). The arbitrage pricing theory: Is it testable? *Journal of Finance* 37, 1129-1140.

Shanken, J. (1985). Multi-beta CAPM or equilibrium-APT? A reply. *Journal of Finance* 40, 1189-1196.

Shanken, J. (1992). On the estimation of beta pricing models. *Review of Financial Studies* 5, 1-33.

Shanken, J. and Weinstein, M. (1987). Macroeconomic variables and asset pricing: estimation and tests. Working Paper, University of Rochester.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance* 19, 425-442.

Sharpe, W. F. (1982). Factors in NYSE security returns, 1931-1979. *Journal of Portfolio Management* 8, 5-19.

Speight, A. E. H., McMillan, D. G. and ap Gwilym, O. (2000). Intraday volatility components in FTSE 100 stock index futures. *Journal of Futures Markets* 20, 425-444.

Stekler, H. O. (1967). Data revisions and economic forecasting. *Journal of American Statistical Association* 62, 470-483.

Tauchen, G. E. and Pitts, M. (1983). The price variability-volume relationship on speculative markets. *Econometrica* 51, 485-505.

Tauchen, G. and Zhou, H. (2005). Identifying realized jumps on financial markets. Unpublished manuscript.

Taylor, N. (2004). Modeling discontinuous periodic conditional volatility: evidence from the commodity futures market. *Journal of Futures Markets* 24, 805-834.

Taylor, S. J. (1986). Modelling financial time series. Chichester: John Wiley and Sons.

Taylor, S. J. and Xu, X. (1997). The incremental volatility information in one million foreign exchange quotations. *Journal of Empirical Finance* 4, 317-340.

Thomakos, D. D. and Wang, T. (2003). Realized volatility in the futures markets. *Journal of Empirical Finance* 10, 321-353.

Tse, Y. K. (1991). Stock returns volatility in the Tokyo stock exchange. *Japan and the World Economy* 3, 285-298.

Tse, Y. (1999). Market microstructure of FTSE 100 index futures: an intraday empirical analysis. *Journal of Futures Markets* 19, 31-58.

Tse, Y. K. and Tung, S. H. (1992). Forecasting volatility in the Singapore stock market. *Asia Pacific Journal of Management* 9, 1-13.

Vilasuso, J. (2002). Forecasting exchange rate volatility. *Economics Letters* 76, 59-64.

West, K. D. and Cho, D. (1995). The predictive ability of several models of exchange rate volatility. *Journal of Econometrics* 69, 367-391.

White, H. (1980). A heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity. *Econometrica* 48, 817-838.

Wood, R. A., McInish, T. H. and Ord, J. K. (1985). An investigation of transactions data for NYSE stocks. *Journal of Finance* 40, 723-739.

Zellner, A. (1958). A statistical analysis of provisional estimates of gross national product and its components, of selected national income components, and of personal saving. *Journal of the American Statistical Association*, 53, 54-65.

Zhang, L., Mykland, P. A. and Aït-Sahalia, Y. (2005). A tale of two time scales: Determining integrated volatility with noisy high frequency data. *Journal of the American Statistical Association* 100, 1394-1411.