Modelling and forecasting stock and stock market volatility.

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MODELLING AND FORECASTING STOCK AND STOCK MARKET VOLATILITY

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UNIVERSITY OF WALES, SWANSEA

2001

Summary of Thesis

Candidate's Surname: Gower
Candidate's Forenames: Craig Paul
Institution/College at which study pursued: University of Wales, Swansea
Candidature for the Degree of PhD
Full Title of Thesis: Modelling and Forecasting Stock and Stock Market Volatility

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Summary:

The examination of stock price volatility has come under increased scrutiny due to the large swings in stock price movements that have occurred with greater frequency than the historical average. Additionally, the substantial increases in the volume of options trading has increased the importance of accurate volatility forecasts due to the volatility forecast being the most important parameter affecting the pricing of options. Consequently, the aim of the thesis is to analyse the volatility of forty-five FTSE 100 stocks, the FTSE 100 index together with other major and emerging market stock indices. In particular, a comparison of the modelling and forecasting ability of GARCH type and stochastic volatility models is undertaken. The forecasting ability of the above models is compared against three benchmark models: the historical mean, random walk and exponential smoothing models. In terms of forecasting, the thesis is of interest because there have been few comparative studies for individual UK stocks. Additionally, the volatility-volume relationship is also considered in order to test the mixture of distributions hypothesis rationalisation for GARCH. In an extension of the current volatility volume literature, the CGARCH-volume model is used to examine the temporary volatility volume interactions. In terms of modelling ability, the stochastic volatility model performs on a par with the GARCH type models. In the forecasting analysis, the daily forecasts of FTSE 100 stocks perform poorly against the benchmark models with the four-weekly volatility forecasts performing relatively better. For the indices, the GARCH type models perform substantially better than for the FTSE 100 stocks.

Declaration

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

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STATEMENT 1

This thesis is the result of my own investigations, except where otherwise stated. Other sources are acknowledged by citation giving explicit references. A bibliography is appended.

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Chapter 1 - Introduction

Uncertainty is central to much of contemporary finance theory, and stock price volatility has come under increased scrutiny due to the large swings in stock price movements that have occurred with higher frequency than the historical average. Institutional changes such as program trading and the introduction of derivative futures and options are often mooted as the likely cause of this. Consequently, greater recognition has been given to the importance of accurate volatility estimates because of their critical role in the pricing of derivative futures and option contracts. This has led to the development of many new econometric models that allow for time-varying variances and covariances.

Mandelbrot (1963a, 1963b and 1967) finds that the unconditional distributions of asset prices have thick tails, time-varying variances and volatility clustering. The ARCH (autoregressive conditional heteroscedasticity) model of Engle (1982) is the first formal model for characterising time-varying variances. The model captures the phenomena of volatility clustering and kurtosis i.e. asset return distributions tend to be thick-tailed. The generalised ARCH (GARCH) model of Bollerslev (1986) provides a parsimonious representation for the conditional variance by introducing a lag structure of past conditional variances. Nevertheless, ARCH and GARCH models do not account for all the kurtosis found in financial variables, and numerous refinements and extensions of the GARCH framework have been proposed. Nonlinear models such as the exponential GARCH (EGARCH) model of Nelson (1991) and the threshold-GARCH (GJR) model of Glosten, Jagannathan and Runkle (1993) are able to capture any asymmetric response of volatility to past shocks. Engle and Lee

(1993) propose the component GARCH (CGARCH) model, where the conditional variance is decomposed into permanent and transitory components. These components help to explain the long-run and short-run movements of stock market volatility, and the model can be further extended to the nonlinear asymmetric CGARCH (ACGARCH) model. Taylor (1986) formulates the stochastic volatility (SV) model. The key feature of the model is that unlike GARCH type models, both the mean and log-volatility have separate error terms. The conditional volatility does not depend on past observations, but on some unobserved components or latent structure.

The aim of the thesis is to give a detailed analysis of the volatility of stock and stock market indices for a ten year period between 1988 and 1998. In particular, a comparison of the modelling and forecasting ability of GARCH type and stochastic volatility models is undertaken. The forecasting ability of the models is assessed by comparing the volatility forecasts to those of the historical mean, random walk and exponential smoothing models. The optimal volatility forecasting model tends not to be the same for different time frequencies. In order to examine this issue, forecasts for daily and four-weekly data will be carried out. For the FTSE 100 companies, it would be expected that the GARCH class models will give a relatively poor forecast performance for daily data. This is because the inherent noise in the return generating process will reduce the explanatory power of the GARCH class volatility models. For the four weekly data, the effect of the noise in the return process can be reduced by using daily data to evaluate the true volatility. It would then be expected that the GARCH class models would give a relatively better forecasting performance against the benchmark models.

For the indices, the inherent noise in the return generating process of the individual companies tends to average out due to the large numbers of constituent stocks. Therefore, it would be expected that the GARCH type models would give relatively better daily forecasts of volatility. Examining the indices gives the opportunity to see whether the conclusions about the volatility of U.K. based stocks can be extended to the international stock markets. It also enables a comparison of the characteristics of stock market volatility between the major indices and the emerging market indices. An index by its construction, smooths the volatility of the individual stocks that act as its constituents. This feature can result in quite different conclusions on the best model as compared with the individual stocks. Therefore, comparisons of the overall performance of the models can reveal their suitability for modelling the volatility of individual stocks as opposed to stock indices and vice versa. Volatility forecasting has direct relevance to the pricing of options, and assessing the strengths and weaknesses of the models in question can lead to an improved choice of pricing model. In terms of forecasting, the thesis is of interest because there have been few comparative studies for individual UK stocks.

The volatility volume relationship is also considered, that is, whether GARCH effects in stock returns can be explained by temporal dependence in the volume of trade. The volatility volume analysis is also extended to CGARCH models, this adds to the literature on volatility volume models because work using this model has not been undertaken before. The analysis also acts as a test of the mixture of distributions hypothesis (MDH) of Clark (1973) which is a rationalisation for GARCH effects. In this model the flow of information is a latent common factor that affects both daily stock returns and trading volume. Stock price changes would then follow a mixture of distributions in which the speed of information flow is the mixing variable. If the MDH proves inadequate, this provides a justification for the use of stochastic volatility models. Andersen (1994, 1996) states that one interpretation of the latent volatility process of the stochastic volatility model is that it represents a random and uneven flow of information. The modified MDH could be more in keeping with financial returns data.

The structure of the remaining chapters is as follows: Chapter two details the properties and the empirical evidence relating to the GARCH type models. The third chapter provides a comparative evaluation of the modelling ability of GARCH/GJR and CGARCH/ACGARCH models for the Financial Times-Stock Exchange 100 (FTSE 100) index and thirty–nine of its constituent stocks. The aim of the chapter is to find whether certain models consistently outperform the others. Following on from this, chapter four examines the ability of the above models to forecast volatility. Chapter five examines the volatility-volume relationship and tests for the presence of the MDH. Following on from this, Chapter six extends the analysis by looking at the modelling and forecasting ability of stochastic volatility models in comparison with GARCH type models. In order to complete a broader analysis of stock market volatility, the analysis is further extended in chapter seven to cover six major international stock market indices and four emerging market stock market indices. Finally, chapter eight details the conclusions from the analysis.

Chapter 2 - Literature Review of GARCH type Models

2.1 Introduction

Uncertainty is central to much of contemporary finance theory; this has led to the development of many new econometric models that allow for time varying variances and covariances.

Mandelbrot (1963a, 1963b and 1967) finds that the unconditional distributions of asset prices have thick tails, time-varying variances and large (small) changes tending to follow large (small) changes of either sign. This prompted researchers to use informal methods of modelling time varying variances. For example, Mandelbrot (1963) uses recursive estimates of the variance over time and Klein (1977) takes five period moving variance estimates about a ten period moving sample mean.

The ARCH (autoregressive conditional heteroscedasticity) model of Engle (1982) is the first formal model that emerged for characterising time-varying variances. The model captures the phenomenon of volatility clustering and it has an unconditional distribution for the error which displays kurtosis. Nevertheless, it still does not adequately account for the kurtosis found in many financial time series. It is also computationally burdensome as a large number of lags are required. The generalised-ARCH (GARCH) model of Bollerslev (1986) solves the problem of an excessive number of lags, although it still does not account for all of the kurtosis found in financial variables. Also, the linearity assumption of ARCH and GARCH models restrict their suitability for a number of financial time series.

Nonlinear models such as the exponential GARCH (EGARCH) model of Nelson (1991), the threshold-GARCH model of Glosten, Jagannathan and Runkle (1993) and the quadratic ARCH (QARCH) model of Sentana (1995) are able to capture any asymmetric response of volatility to past shocks. These models more adequately account for the excess kurtosis found in financial time series. The EGARCH and QARCH models can also be used to measure the volatility feedback effect, that is, the tendency that an unusually large realisation of news, good or bad, increases future expected volatility, which in turn lowers the price of the asset.

A remaining problem of the above models is that they give distinctly different levels of volatility persistence for high frequency as opposed to lower frequency data. The persistence of high frequency volatility shocks tends to be measured in hours as compared to months for the lower frequency data. This paradox can be resolved by the use of volatility component models. Anderson and Bollerslev (1996) suggest that market volatility reflects the aggregation of a number of volatility components resulting from the arrival of heterogeneous information. The model is an extension of the mixture of distributions hypothesis (MDH) of Clark (1973) which states that price changes are sampled from a set of distributions with different variances due to differences in the rate of information arrival. In the Anderson and Bollerslev model, over longer time periods the short-run processes decay rapidly, while the more persistent processes remain significant. The conflicting results on volatility persistence are explained by the fact that the rapid decay of the short-run processes are more noticeable over higher frequencies, whereas over the longer term, only the highly persistent processes stand out. Unfortunately, it would be difficult to link specific volatility components to the factors generating the information flows, this is even more so for high frequency data. An easier model to analyse empirically is the unobserved component model of Engle and Lee (1993), where the conditional variance is decomposed into permanent and transitory components. These components help to explain the long-run and short-run movements of stock market volatility. An alternative viewpoint is given by Müller et al. (1997). They perceive that it is the diversity of market agent types that cause the volatilities of different time resolutions to behave differently. Long-term traders evaluate the market at a lower frequency and have a longer memory than short-term traders. As a result, volatility is divided into components in a similar way to the permanent and transitory volatility components model of Engle and Lee (1993).

There are a number of papers that examine the link between volatility persistence in individual stock returns and the rate of information arrival. The MDH model of Clark (1973) suggests that trading volume, which acts as a proxy for the rate of information arrival, can explain the volatility persistence of stock returns. If this holds, ARCH would simply be a manifestation of the daily time dependence in the rate of information arrival to the market for individual stocks.

The remainder of the chapter is organised as follows. Section 2 details the structure and properties of the various models characterising the conditional variance of asset returns. Section 3 details the empirical evidence relating to the above models. Section 4 offers some concluding remarks.

2.2 Models

2.2.1 The ARCH Model

Following the work of Engle (1982), all discrete time stochastic processes $\{\epsilon_t\}$ of the following form are referred to as constituting an ARCH model:

$$\epsilon_t = Z_t\sqrt{h_t} \tag{2.2.1}$$

$$Z_t,\ Z_t \sim I.I.D.(0,\ 1) \tag{2.2.2}$$

with $\sqrt{h_t}$ a time-varying, positive, and measurable function of the time t-1 information set. The term I.I.D. denotes identically and independently distributed. By definition ϵ_t is serially uncorrelated with mean zero, a constant unconditional variance, and a conditional variance h_t. Generally, ϵ_t corresponds to the innovation in the mean for some other stochastic process, say $\{y_t\}$, where the dependent variable y_t is assumed to be generated by:

$$y_t = x'_t\xi_k + \epsilon_t \quad \text{for } t = 1, \ldots, T \tag{2.2.3}$$

Equation (2.2.3) is known as a dynamic regression model, where x_t is a (k x 1) vector of exogenous variables, which may include lagged values of the dependent variable, and ξ_k is a (k x 1) vector of regression parameters. The ARCH model characterises the distribution of the stochastic error ϵ_t conditional on the realised values of the set of variables $\Psi_{t-1} = \{y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2}, \ldots\}$. Engle's ARCH model assumes:

$$\epsilon_t \mid \Psi_{t-1} \sim N(0,\ h_t) \tag{2.2.4}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 = \omega + \alpha(L)\epsilon_t^2 \tag{2.2.5}$$

where $\omega > 0$, $\alpha_i \geq 0$, and L denotes the lag operator. Here h_t is expressed as a linear function of past squared values of the process, and the model is known as the linear ARCH(q) model. Since $\epsilon_{t-i} = y_{t-i} - x'_{t-i}\xi_k$ for $i = 1, \ldots, q$, h_t is clearly a function of the elements of Ψ_{t-1}. Episodes of volatility are generally characterised as the clustering of large shocks to the dependent variable. The ARCH(q) model captures the tendency for volatility clustering, that is, for large (small) price changes to be followed by other large (small) price changes, but of an unpredictable sign. In the regression model, a large shock is represented by a large deviation of y_t from its conditional mean $x'_t\xi_k$, or equivalently, a large positive or negative value of ϵ_t. In the ARCH model, the variance of the current error ϵ_t is an increasing function of the magnitude of the lagged errors, irrespective of their signs. This is due to the fact that the value of the current error is conditional on the values of the lagged errors ϵ_{t-i}, for $i = 1, \ldots, q$. As a result of this, small errors of either sign tend to be followed by small errors of either sign, and likewise for large errors. The order of the lag q determines the length of time for which a shock persists in conditioning the variance of the subsequent errors. The larger the value of q, the longer the episodes of volatility clustering will tend to be.

2.2.2 The GARCH Model

In empirical applications of ARCH(q) models, a long lag is often required. This would involve estimating a large number of parameters subject to inequality restrictions. An alternative and more flexible lag structure is usually provided by the generalised ARCH, or GARCH(p, q), model in Bollerslev (1986):

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} = \omega + \alpha(L)\epsilon_t^2 + \beta(L)h_t \tag{2.2.6}$$

where ω, α_i, and β_i are real and nonnegative parameters. For the GARCH model expressed in equation (2.2.6), it is necessary and sufficient that the sum $\lambda = \Sigma_i \alpha_i + \Sigma_i \beta_i < 1$ in order for the process to be stationary; λ also provides a measure of the persistence of shocks to h_t, with a half-life given by $\varrho = [\ln(0.5)/\ln(\lambda)]$. In empirical investigations of high-frequency data, a high degree of persistence is regularly found when estimating the conditional variance functions. In fact, it is not uncommon to find that the estimated coefficients of the conditional variance sum close to one; this is shown by the presence of an approximate unit root in the autoregressive polynomial, that is, $\alpha_1 + \ldots + \alpha_q + \beta_1 + \ldots + \beta_p = 1$. Engle and Bollerslev (1986) refer to the limiting case, where $\lambda = 1$, as integrated GARCH (IGARCH). In IGARCH models, current information remains important for forecasts of the conditional variance for all horizons. Therefore, a current shock would persist indefinitely in conditioning the future variances. Shocks to the system are permanent. Consequently, the unconditional variance for the IGARCH(p, q) model does not exist, it is infinite. Nelson (1990) shows that although IGARCH models are not weakly stationary, due to their infinite variances, they can be strongly stationary. This is because finite moments are not required for strong stationarity. Strong stationarity only requires that the distribution function of any finite set of residuals is invariant under time translations.

For the conditional variance in the GARCH(p, q) model to be positive the simple restriction is that all the coefficients of equation (2.2.8) must be positive, that is, $\omega > 0$, $\alpha_i \geq 0$ for $i = 1, \ldots, q$ and $\beta_i \geq 0$ for $i = 1, \ldots, p$. Nelson and Cao (1992) have shown that the restrictions need not be imposed in estimation, as violation of these inequalities does not necessarily imply that the conditional variance function is misspecified. For example, in a GARCH (1,2) process, $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\beta_1 \alpha_1 + \alpha_2 \geq 0$ are sufficient to guarantee that $h_t > 0$. Therefore in the GARCH (1, 2) model α_2 may be negative. Additional restrictions are that the process is stationary and that $\alpha(L)$ and $\beta(L)$ must have no common roots.

Provided that the GARCH(p, q) process is stationary, it can be given an infinite order ARCH representation, since equation (2.2.6) can be rewritten as:

$$h_t = \frac{\omega}{(1 - \beta(L))} + \frac{\alpha(L)}{(1 - \beta(L))} \epsilon_t^2 \qquad (2.2.7)$$

$$h_t = \omega^* + \sum_{i=1}^{\infty} \delta_i \epsilon_{t-i}^2 \qquad (2.2.8)$$

where $\omega^* = \omega/(1 - \beta(L))$ and the coefficient δ_i is the coefficient of L^i in the expansion of $\alpha(L)[1 - \beta(L)]^{-1}$.

The GARCH(p, q) model can be also given an ARMA[max(p, q), p] representation (where ARMA stands for autoregressive moving average) by substituting $V_t = \epsilon_t^2 - h_t$ into equation (2.2.6):

$$\epsilon_t^2 - V_t = \omega + \alpha(L)\epsilon_t^2 + \beta(L)(\epsilon_t^2 - V_t)$$

$$\epsilon_t^2 = \omega + [\alpha(L) + \beta(L)]\epsilon_t^2 - \beta(L)V_t + V_t \qquad (2.2.9)$$

The ARMA model for ϵ_t^2 has autoregressive parameters $[\alpha(L) + \beta(L)]$, moving average parameters $-\beta(L)$, and serially uncorrelated innovation sequence $\{\epsilon_t^2 - h_t\}$. This analogy to the ARMA class of models allows for the use of standard time series techniques in the identification of the orders of p and q. Generally, the GARCH(1, 1) process has been able to represent the majority of financial time series. It is very rare that a time series requires a model of order greater than GARCH(2, 2). This is because the introduction of lagged conditional variance terms capture higher order lags in ϵ_t^2. This gives the GARCH(p, q) models an infinite order ARCH(q) representation.

The ARCH(q) and GARCH(p, q) models have unconditional distributions for ϵ_t with conditionally normal errors that have fatter tails than the normal distribution, that is, they have kurtosis. Nevertheless, these models do not adequately account for the kurtosis in many financial time series. This is shown by the standardised residuals from the estimated models often appearing to be leptokurtic. As a consequence, improved models have been developed.

2.2.3 The (G)ARCH-M Model

A number of financial theories call for a trade off between the risk and the expected mean of a return. To deal with this situation Engle, Lilien and Robins (1987) formulated the ARCH in mean, or ARCH-M class of models. The conditional mean is made an explicit function of the conditional variance as given below:

$$y_t = g(x_{t-1}, h_t; \mu) + \epsilon_t \tag{2.2.10}$$

Depending on the sign of the partial derivative of $g(x_{t-1}, h_t; \mu)$ with respect to h_t, an increase in the conditional variance can be associated with either an increase or decrease in the conditional mean. Engle et al. find that logarithmic functions of h_t work best for the estimation of time varying risk premia. Pagan and Hong (1991) state that the use of a logarithmic function can prove to be problematic for $h_t < 1$ and when $h_t \to 0$. This is because as $h_t \to 0$, the effect on y_t will be infinite, as a result of this, a linear function of h_t could prove to be less problematic. Using the conditional mean as an explicit function of the conditional variance can be similarly extended to GARCH models, to give the GARCH-M class of models.

2.2.4 Asymmetric/Nonlinear (G)ARCH Models

The linearity assumption of the ARCH (q) and GARCH (p, q) models restrict their suitability for some situations. Nelson (1991) suggests that they may be inappropriate for modelling the volatility of returns on stocks as their conditional variance functions are symmetric. This is because they cannot represent the phenomenon known as the 'leverage effect', which is the negative correlation between volatility and past returns. Essentially, the ARCH and GARCH models are only a function of the magnitudes of the residuals and not their signs. Nelson begins by making the conditional variance a linear function of time and lagged Z_t's. Therefore, Z_t acts as a forcing variable for both the conditional variance and the error term. A log form is used to ensure that h_t remains nonnegative without the need to constrain the model coefficients:

$$\ln(h_t) = \omega + \sum_{i=1}^{q} \alpha_i g(Z_{t-i}) + \sum_{i=1}^{p} \beta_i \ln(h_{t-i}) \tag{2.2.11}$$

where

$$g(Z_t) = \theta Z_t + \gamma[|Z_t| - E|Z_t|] \tag{2.2.12}$$

The above conditional variance is known as exponential GARCH (EGARCH). The variable $g(Z_t)$ is a zero mean I.I.D. random sequence, thus, equation (2.2.11) follows an ARMA(p, q) process for $\ln(h_t)$ with innovation $g(Z_t)$. The innovation to the conditional variance is linear with slope $\alpha_i(\theta + \gamma)$ over the range $0 < Z_t < \infty$ and $\alpha_i(\theta - \gamma)$ over the range $-\infty < Z_t \leq 0$. This feature produces the asymmetric response to rises and falls in stock price. The above model can also be given the following representation:

$$\ln(h_t) = \omega + \sum_{i=1}^{q} \alpha_i(\theta Z_{t-i} + \gamma|Z_{t-i}|) + \sum_{i=1}^{p} \beta_i \ln(h_{t-i}) \tag{2.2.13}$$

which leads to a different intercept estimate by the amount $-\alpha(\sqrt{(2/\pi)})$ as the term $-E|Z_{t-i}|$ is omitted. Volatility clustering is captured by the term in $|Z_{t-i}|$. When γ is positive, large (small) unexpected changes tend to be followed by further large (small) changes of either sign. Therefore, large shocks increase the conditional variance, whilst the persistence of shocks is given by $\lambda = \Sigma_i\beta_i$, with a half-life calculated as above. The term in Z_{t-i} allows for any correlation between the error and future conditional variances. The leverage effect is captured by a negative value of $\alpha_i\theta$, which allows a positive value of the returns innovation to cause a negative innovation in the conditional variance.

A number of other models have been proposed to represent the asymmetric response of the conditional variance to positive and negative errors. Zakoian (1990) suggests a formulation referred to as a threshold ARCH (TARCH) model. The conditional standard deviation is of the form:

$$\sqrt{h_t} = \omega + \sum_{i=1}^{q} \alpha_i^+ \epsilon_{t-i}^+ - \sum_{i=1}^{q} \alpha_i^- \epsilon_{t-i}^- \tag{2.2.14}$$

where $\epsilon_t^+ = \max\{\epsilon_t, 0\}$ and $\epsilon_t^- = \min\{\epsilon_t, 0\}$, $\omega > 0$, $\alpha_1^+ \geq 0$, and $\alpha_1^- \geq 0$ for $i = 1, \ldots, q$.

The conditional standard deviation is linear in ϵ_{t-i} with slopes α_i^+ when ϵ_{t-i} is positive and α_i^- when ϵ_{t-i} is negative. This is the source of the asymmetry in the conditional variance.

Glosten, Jagannathan and Runkle (1993) also propose a threshold ARCH specification to capture both volatility clustering and the leverage effect by adding a term for the asymmetry to the GARCH model. The GJR(p, q) model is given by:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} \tag{2.2.15}$$

where the asymmetry effect is captured by the use of the dummy variable D_{t-1}, such that $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. This allows good news ($\epsilon_t > 0$) to have an impact of α, while bad news ($\epsilon_t < 0$) has an impact of $\alpha + \gamma$. If $\gamma \neq 0$ the news impact is asymmetric, while a positive value of γ indicates that the leverage effect exists. The GJR(p,q) model nests the GARCH(p, q) model, for which γ is restricted to zero. The persistence of shocks to the conditional variance is quantified by $\lambda = \Sigma_i \alpha_i + \Sigma_i \beta_i + (\gamma_1/2)$, with a half-life calculated as above.

Sentana (1995) also introduces a model which captures dynamic asymmetry, it is the most general quadratic version possible of the ARCH class of models. It encompasses all the existing restricted quadratic variance functions. The model is known as quadratic ARCH (QARCH), and nests the augmented ARCH model of Bera and Lee (1990), the asymmetric ARCH model in Engle (1990) and the linear 'standard deviation' model discussed by Robinson (1991).

$$h_t(\epsilon_{t-1}, q) = \omega + \sum_{i=1}^{q} \psi_i \epsilon_{t-i} + \sum_{i=1}^{q} a_{ii} \epsilon_{t-i}^2 + 2\sum_{i=1}^{q} \sum_{j=i+1}^{q} a_{ij} \epsilon_{t-i} \epsilon_{t-j}$$
$$= \omega + \psi' \epsilon_{t-1,\, q} + \epsilon'_{t-1,\, q} A \epsilon_{t-1,\, q} \tag{2.2.16}$$

where ψ is a (q x 1) vector, A is a symmetric (q x q) matrix. The persistence of shocks to the conditional variance is given by $\lambda = \Sigma_i a_{ii}$, with a half-life calculated as above. To obtain the nested models, certain restrictions are made on the parameters of the conditional variance function. The ARCH model of Engle (1982) assumes that $\psi = 0$ and that A is diagonal, whereas the augmented ARCH only requires that $\psi = 0$. The linear standard deviation model assumes that $h_t = (\iota + \varsigma' \epsilon_{t-1,\, q})^2$ which implies that $\omega = \iota^2$, $\psi = 2\iota\varsigma$ and $A = \varsigma\varsigma'$. The theoretical results of these models will generally hold with only minor modifications for the QARCH model.

One benefit of the QARCH model is that it has a nondiagonal 'A', this specifies an ARCH process with additional cross-product terms between the past errors. The cross-product terms take account of the effect of the interaction between the lagged residuals on the conditional variance. The major advantage of the QARCH formulation is that it allows ψ to take any value. As a consequence, an asymmetric effect of positive and negative values is allowed as the quadratic polynomial for h_t is not centred at zero. For example, consider the QARCH (1) model:

$$h_t = \omega + \psi_1 \epsilon_{t-1} + a_{11} \epsilon_{t-1}^2 \tag{2.2.17}$$

where ψ_1 measures dynamic asymmetry; if ψ_1 is negative, the unconditional variance will be higher when ϵ_{t-1} is negative than when it is positive. This allows the model to capture the 'leverage effect'.

As with ARCH(q) models, applications of the QARCH(q) models generally require long lags. Generalised QARCH, or GQARCH(p, q) models offer a more parsimonious approximation to the conditional variance function by including lagged values of the conditional variance. The GQARCH model is given by:

$$h_t = \omega + \psi' \epsilon_{t-1,\,q} + \epsilon'_{t-1,\,q} A \epsilon_{t-1,\,q} + \sum_{i=1}^{p} \beta_i h_{t-i} \qquad (2.2.18)$$

The persistence of shocks to the conditional variance is modified by the inclusion of the coefficients of the lagged conditional variance terms. It is given by $\lambda = \Sigma_i a_{ii} + \Sigma_i \beta_i$, with a half-life calculated as above.

Sentana stated that the properties of GARCH(1, 1) and GQARCH(1, 1) are remarkably similar. They both have the same mean, variance and autocorrelation functions for both the series and its squares, as well as the same forecasting recursion. The GQARCH(1, 1) has the advantage that with a single extra parameter, ψ_1, it allows for an asymmetric effect on the conditional variance. The additional term also allows higher unconditional kurtosis. As mentioned earlier, the GARCH(p, q) model does not adequately account for the level of kurtosis in many financial time series. Therefore, the GQARCH(p, q) model is more representative of the characteristics of many financial time series.

2.2.5 Volatility Component Models

Following Engle and Lee (1993), the multi-step forecast of the variance conditional on Ψ_{t-1}, is defined as $h_{t+k} \equiv var(y_{t+k} \mid \Psi_{t-1})$. Provided y_t is a covariance stationary process, that is,

$(\alpha + \beta) < 1$, the multi-step forecast of the conditional variance in the GARCH(1, 1) model is given by:

$$h_{t+k} = \omega \frac{[1 - (\alpha + \beta)^k]}{(1 - \alpha - \beta)}$$
$$= \frac{\omega}{(1 - \alpha - \beta)} \qquad \text{as } k \to \infty \tag{2.2.19}$$

which converges to the unconditional variance $\sigma^2 \equiv Var(y_t)$. Therefore, the GARCH(1, 1) model can be rewritten as:

$$h_t = \sigma^2 + \alpha(\epsilon_{t-1}^2 - \sigma^2) + \beta(h_{t-1} - \sigma^2) \tag{2.2.20}$$

where the two terms in parentheses have an expected value of zero, this reflects volatility being constant in the long-run. Engle and Lee (1993) decompose the conditional variance into a permanent component and a transitory component which is mean-reverting towards the trend component. The time-varying permanent component acknowledges the possibility that long-run volatility is not constant. The two components help to explain the long-run and short-run movements of stock market volatility. The model is given by:

$$h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1} - q_{t-1}) \tag{2.2.21}$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1}) \qquad \text{for } \rho < 1 \text{ and } (\alpha + \beta) < 1 \tag{2.2.22}$$

where q_t is the permanent component (trend) of the conditional variance which is defined as an integrated process plus a constant drift and ρ is an autoregressive unit root. The forecasting error,

$(\epsilon_t^2 - h_t)$, acts as the driving force for the time-dependent movement of the trend. The transitory component of the conditional variance is defined as the difference between the conditional variance and its trend, $(h_t - q_t)$. The initial effect of a shock to the transitory component is given by α, β quantifies the level of memory in the transitory component, while the sum of the two parameters $(\alpha + \beta)$ represents the persistence of transitory shocks. Likewise, the initial impact of a shock to the permanent component is given by ϕ, with the level of persistence being quantified by the autoregressive root, $0 < (\alpha + \beta) < \rho \leq 1$, which encompasses the case of integration in volatility for values of ρ equal to unity. The conditional variance is covariance stationary if the transitory and permanent components are stationary, as denoted by $\rho < 1$ and $(\alpha + \beta) < 1$ respectively. Provided that $(\alpha + \beta) < \rho < 1$, the permanent component will dominate forecasts of the conditional variance as the forecasting horizon is extended. By substituting (2.2.22) into (2.2.21) and using (2.2.22) once more, Engle and Lee show that the component model can be expressed as a GARCH(2, 2) model, or as a GARCH(1, 1) process with a time varying intercept, the latter is given by:

$$h_t = [\omega + (\rho - \alpha - \beta)q_{t-1}] + (\alpha + \phi)\epsilon_{t-1}^2 + (\beta - \phi)h_{t-1} \qquad (2.2.23)$$

Provided that q_t is non-negative, the conditional variance will be non-negative if $\omega > 0$, $\alpha > 0$, $\beta > \phi > 0$, $1 > \rho > (\alpha + \beta) > 0$. The permanent component can also be expressed as a GARCH(2, 2) model, and Engle and Lee demonstrate that non-negativity of the permanent component is satisfied under the same constraints as that of non-negativity of the conditional variance.

Engle and Lee (1993) also construct an asymmetric component model to examine the 'leverage effect'. The dummy variable approach of Glosten, Jagannathan and Runkle (1993) is used to allow shocks to affect the volatility components asymmetrically. Let D_t be a dummy variable: $D_t = 1$ if $\epsilon_t < 0$ and $D_t = 0$ if $\epsilon_t > 0$. The component model becomes:

$$h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) \quad (2.2.24)$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1}) + \delta_l(D_{t-1}\epsilon_{t-1}^2 - 0.5h_{t-1}) \quad (2.2.25)$$

For $\rho < 1$ and $(\alpha + \beta) < 1$, δ_l and δ_s represent the long-run and short-run leverage effects. The initial effect of a shock to the transitory component is given by α in the case of good news while the impact of bad news is given by $\alpha + \delta_s$. The persistence of transitory shocks is quantified by $\alpha + \beta + (\delta_s/2)$. The leverage effect in the long-run should be zero as a firm is able to adjust its capital structure in the long-run. Consequently, the effect of a shock to the permanent component is quantified by ϕ with a persistence level given by ρ.

2.2.6 (G)ARCH Rationalisations

2.2.6.1 Random Coefficient Model

One of the central reasons why Engle (1982) formulates the ARCH model is that the ability to forecast the future varies from one period to the next. This uncertainty can be expressed as a random coefficient formulation. Bera and Lee (1993) formulate the following random coefficient process:

$$\epsilon_t = \sum_{i=1}^{q} \zeta_{it}\epsilon_{t-i} + u_t \quad (2.2.26)$$

$$\epsilon_t = \sum_{i=1}^{q} (\zeta_i + \eta_{it})\epsilon_{t-i} + u_t \quad (2.2.27)$$

where $\eta_t = (\eta_{1t}, \ldots, \eta_{qt})' \sim (o, A_{q \times q})$, $u_t \sim (0, \sigma_u^2)$ are independent and the η_t coefficients are randomly selected from the q different values. Given the information available, Ψ_{t-1}, it follows that:

$$E(\epsilon_t | \psi_{t-1}) = \zeta' \hat{\epsilon}_{t-1} \tag{2.2.28}$$

where $\zeta = (\zeta_1, \ldots, \zeta_q)'$ and $\hat{\epsilon}_{t-1} = (\epsilon_{t-1}, \ldots, \epsilon_{t-q})'$. The conditional variance is given by:

$$Var(\epsilon_t | \psi_{t-1}) = \hat{\epsilon}_{t-1}' A \hat{\epsilon}_{t-1} + \sigma_u^2 \tag{2.2.29}$$

If $A = ((\alpha_{ij}))$ is a diagonal matrix with $A = diag(\alpha_1, \ldots, \alpha_q)$ and $\sigma_u^2 = \omega$, then the random coefficient process can be interpreted as an ARCH(q) process as given by:

$$Var(\epsilon_t | \Psi_{t-1}) = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \tag{2.2.30}$$

Equation (2.2.29) is the augmented ARCH model of Bera and Lee (1990). The introduction of cross product terms to equation (2.2.29) gives the quadratic ARCH model of Sentana (1995). This shows that the ARCH class of models is able to capture the randomness due to uncertainty.

2.2.6.2 Time Deformation Model

Stock (1988) notes the similarities between his time deformation model and ARCH models. Stock puts forward the idea that economic variables evolve on a data-based rather than a calendar based time-scale. The measuring of economic variables by a calendar based time-scale results in time-varying model parameters which are conditionally heteroscedastic. Volatility clustering arises because the actual variable may evolve more quickly or slowly as compared to the calendar time-scale. Stock shows that for small time deformations, his model can be approximated by:

$$\epsilon_t = \rho_t \epsilon_{t-1} + \nu_t \tag{2.2.31}$$

$$h_t = \omega + \alpha_1 \epsilon_{t-1}^2 \tag{2.2.32}$$

where conditional on the information available, ν_t is normally distributed with a mean of zero and a conditional variance of h_t. The only difference between the above model and an ARCH(1) model is the inclusion of the time-varying autoregressive parameter, ρ_t. However, this variable is a central feature of the model and is linked to the time-scale transformation. The conditional mean variables in the above model vary over time due to their dependence on the time-scale transformation. Stock shows that the autoregressive parameter is inversely related to the conditional variance, that is, ρ_t is large and h_t is small when a long segment of operational time has passed during a unit of calendar time.

2.2.6.3 A Conditional Mixture Model

It has long been recognised that the variance of stock price changes may be related to trading volume. Clark (1973) suggests a mixture of distributions model where information flow is a latent common factor that affects both daily stock returns and trading volume. Stock price changes would then follow a mixture of distributions in which the speed of information flow is the mixing variable. Following on from this Gallant, Hsieh and Tauchen (1991) formulate a model to explain the good performance of the ARCH models.

Consider the observed price change of an asset, R_t, which is defined as:

$$R_t = \mu_t + \sum_{i=1}^{I_t} s_i \tag{2.2.33}$$

where s_i is I.I.D. distributed with a mean of zero and a variance of τ^2. Here, μ_t is the forecastable component, the s_i's are the incremental price changes and I_t is the number of information arrivals to the market in period t. I_t is assumed to be independent of the s_i's and is a serially correlated unobservable random variable. R_t is distributed as a mixture of normal distributions due to the random nature of I_t. It is generated by a subordinated stochastic process in which R_t is subordinate to s_i, and I_t is the directing process. Equation (2.2.33) can be written as:

$$R_t = \mu_t + \tau\sqrt{I_t}z_t \tag{2.2.34}$$

Then, conditional on the number of information arrivals, I_t, R_t will be normally distributed with mean μ and a variance which is proportional to I_t. $R_t \mid I_t \sim N(\mu_t, \tau^2 I_t)$. The conditional variance is given by:

$$E[(y_t - \mu_t)^2 \mid \Psi_{t-1}] = \tau^2 E[I_t \mid \Psi_{t-1}] \tag{2.2.35}$$

where Ψ_{t-1} is the available information set. Let $y_t - \mu_t = \tau\sqrt{I_t}\, z_t$ be the error ϵ_t. The auto-covariances of the squared errors are given by:

$\sqrt{I_t}$

$$\begin{aligned} Cov(\epsilon_t^2, \epsilon_{t-j}^2) &= \tau^4\, Cov(I_t Z_t^2, I_{t-j} Z_{t-j}^2) \\ &= \tau^4\, Cov(I_t, I_{t-j}) \end{aligned} \tag{2.2.36}$$

Thus, if the I_t's are serially dependent, the squared errors will be correlated. The ARCH class of models is able to capture this correlation. If no serial correlation was present in the information arrivals process, then price changes would not exhibit ARCH patterns, thereby making the model irrelevant.

2.2.6.4 Heterogeneous Information Arrivals Model

Anderson and Bollerslev (1996) formulate a heterogeneous information arrivals model which is an extension of the MDH model of Clark (1973). They interpret the overall market volatility as the manifestation of numerous information arrival processes, some with highly persistent volatility patterns, others only possessing short-run volatility dependencies. Over longer time periods the short-run processes decay significantly, while the highly persistent processes still remain influential. Essentially, the rapid decay of the short-run processes stands out most clearly over the higher frequencies, whereas over the longer-term only the highly persistent processes will be noticeable. This explains how the level of volatility persistence is measured in hours for high frequency data as compared to months for lower frequency observations. Basically, the process behaves as if it is fractionally integrated.

The following representation for the high frequency returns is used:

$$R_t = r_t - m_t = \sqrt{W_t} Z_t \tag{2.2.37}$$

where m_t denotes the conditional mean of the raw returns, r_t. W_t is a non-negative, positively serially correlated mixing variable, which serves as a proxy for the aggregate amount of information flow to the market. The conditional variance of the return is given by $Var_{t-1}(R_t) = Var_{t-1}(r_t) = W_t$. The volatility process reflects the aggregate impact of N distinct information arrival processes, $w_{j,t} \geq 0$, where $j = 1, 2, \ldots, N$. The temporal dependence of each constituent component is expressed as follows:

$$w_{j,t} = \alpha_j w_{j,t-1} + \epsilon_{j,t} \tag{2.2.38}$$

where $w_{j,t} \equiv \ln(W_{j,t}) - \mu_j$, $\mu_j \equiv E[\ln(W_{j,t})]$, the $\epsilon_{j,t}$'s are assumed to be I.I.D. normally distributed with a mean of zero and a variance of h_j for all j, $j = 1, \ldots, N$. $W_{j,t} = \exp(w_{j,t} + \mu_j)$ is strictly positive due to the logarithmic formulation. $W_{j,t}$ is the number of information arrivals dictated by the j'th component process. The coefficient α_j reflects the degree of persistence in the j'th information arrival process. The combined effect of the individual information arrival processes on the aggregate latent volatility process is represented as follows:

$$W_t = \exp(w_t + \mu_w) \tag{2.2.39}$$

where $w_t \equiv \sum_{j=1}^{N} w_{j,t}$ and $\mu_w \equiv \sum_{j=1}^{N} \mu_j$. Anderson and Bollerslev find that for a large enough j the autocorrelations for the aggregate volatility process behave like $\rho(w_t, j) \sim j^{1-q}$, where $\rho(w, j)$ denotes the j'th order autocorrelation for w_t. Therefore, the dependence in w_t will dissipate at the slow hyperbolic rate of decay associated with the covariance stationary fractionally integrated, or I(d) class of models, with d = 1 - q. Anderson and Bollerslev state that the volatility process exhibits the same form of long-memory dependence irrespective of the sampling interval.

This is because the long-memory dependence arises through the interaction of a large number of individual information processes, it is inherent to the returns generating process.

2.2.6.5 Heterogeneous Agents Model

Müller et al. (1997) offer a different perspective. They propose that it is the diversity of agents in a heterogeneous market that makes the volatilities of various time resolutions behave differently. Essentially, the variety of market agent types or components perceive, react to, and cause different types of volatility. Short-term traders evaluate the market at a higher frequency and have a shorter memory than long-term traders. As a consequence, volatility is divided into components in a similar way to the permanent and transitory volatility components model of Engle and Lee (1993). Müller et al. use the lagged correlation coefficient to reveal any causal relations and information flows between data of different time resolutions. They find that coarsely defined volatility predicts finely defined volatility significantly better than the other way around. This arises because the level of coarse volatility matters to short-term traders as it determines the scope of trading opportunities by affecting the expected size of trends. Short-term traders react to clusters of coarse volatility by changing their trading behaviour and thus causing clusters of fine volatility. The level of volatility is mostly ignored by long-term traders. Müller et al. propose a HARCH (heterogeneous interval, autoregressive conditional heteroscedasticity) process to model the asymmetric behaviour of fine and coarse volatilities. The returns of a HARCH(n) process are given by:

$$r_t = Z_t\sqrt{h_t} \tag{2.2.40}$$

$$h_t = \omega + \sum_{j=1}^{n} c_j [\sum_{i=1}^{j} r_{t-i}]^2 \tag{2.2.41}$$

where $\omega > 0$, $c_n > 0$, $c_j \geq 0$ for $j = 1, \ldots, n - 1$. The variance is defined as the linear combination of the squares of the aggregated returns. The HARCH process is unique in the ARCH family in that it considers the volatilities of price changes measured over different interval sizes. In HARCH processes the sign of the returns and not just their absolute values matter. A lower contribution to the variance of the process is made by two price changes that cancel each other out than by two price changes of the same size and sign. The coefficients c_j reflect the relative impact of the various market components with different relevant time intervals. The m market components are associated to some coefficients c_j in a limited range of j. The j ranges are separated by powers of a natural number p, therefore, the interval size of adjacent components differs by a factor of p. The effect of the individual component i on the volatility process is defined as the sum of the impacts of all its coefficients c_j.

$$I_1 = c_1 = C_1 \tag{2.2.42}$$

$$I_i = \sum_{j=p^{i-2}+1}^{p^{i-1}} jc_j = (p - 1)p^{i-2}\frac{p^{i-1} + p^{i-2} + 1}{2}C_i \qquad \text{for I} > 1 \tag{2.2.43}$$

2.3 Selected Empirical Evidence

Due to the vastness of the literature on GARCH type models, the following literature review cannot be exhaustive. The empirical evidence is from articles proposing the original models and from more recent articles on the models in question. Extant reviews of the preceding literature can be found in Bera and Higgins (1993), Bollerslev, Chou and Kroner (1992) and Bollerslev, Engle and Nelson (1994).

2.3.1 Asymmetric/Nonlinear (G)ARCH Models

Glosten, Jagannathan and Runkle (1993) estimate a number of modified GARCH-M models using monthly excess returns for the CRSP (centre for research into security prices) value weighted index for the period 1951:4 to 1989:12 in order to arrive at the ideal model specification. The first model estimated is the standard GARCH(1, 1)-M process for stock returns where positive and negative unanticipated returns have the same effect. The model is given by:

$$y_t = \mu + \delta h_{t-1} + \epsilon_t \tag{2.3.1}$$

$$h_{t-1} = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-2} \tag{2.3.2}$$

where $E_{t-1}[\epsilon_t] = 0$ and $E_{t-1}[\epsilon_{t-1}^2] = h_{t-1}$. The second model is a modified GARCH-M model, otherwise known as a GJR(1, 1)-M model. This allows the residual to have an asymmetric impact on the conditional variance.

$$h_{t-1} = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-2} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} \tag{2.3.3}$$

The next model adds the risk-free interest rate to equation (2.3.3) to give:

$$h_{t-1} = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-2} + b_1 r_{ft} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} \tag{2.3.4}$$

The fourth model modifies equation (2.3.3) by adding seasonal dummies for the months January and October as these are found to be particularly volatile months for the stock market in question.

The excess return innovation is a function of a fundamental innovation that does not exhibit any seasonal patterns:

$$\epsilon_t = (1 + \lambda_1 OCT_t + \lambda_2 JAN_t)\dot{\eta}_t \tag{2.3.5}$$

Let $v_{t-1} = E_{t-1}[\dot{\eta}_t^2]$ denote the conditional variance of $\dot{\eta}_t$. The modified model is given by:

$$v_{t-1} = \omega + \alpha_1 \dot{\eta}_{t-1}^2 + \beta_1 v_{t-2} + \gamma_1 \dot{\eta}_{t-1}^2 D_{t-1} \tag{2.3.6}$$

The fifth model adds the risk-free rate to equation (2.3.6) to give:

$$v_{t-1} = \omega + \alpha_1 \dot{\eta}_{t-1}^2 + \beta_1 v_{t-2} + b_1 r_{ft} + \gamma_1 \dot{\eta}_{t-1}^2 D_{t-1} \tag{2.3.7}$$

Glosten, Jagannathan and Runkle (1993) use a number of diagnostics on the estimates of the models; equation (2.3.7) is found to be the most satisfactory. It has a lower level of excess skewness and kurtosis than the other models and the squared standardised residuals of the model are found to be identically and independently distributed. Equation (2.3.7) is the modified GJR(1, 1)-M model, it shows a number of improvements over the standard GARCH(1, 1)-M model. Both the risk-free rate and the seasonals of the GJR model are significant and add to the explanatory power of the model. The GJR model also has a much lower level of excess kurtosis. There is also significant asymmetry in the conditional variance which the variable γ_1 is able to pick up. This suggests that the basic GARCH-M model is misspecified.

The main finding of their model is that there is a negative relation between the conditional expected monthly return and the conditional variance of the monthly return, that is, investors require a relatively smaller risk premium during times when the pay off from a security is more risky. This relation becomes stronger when deterministic monthly seasonals and the risk-free interest rate are included in the conditional variance. They also find that negative residuals are associated with an increase in variance ($\alpha_1 > 0$), while positive residuals are associated with a slight decrease in variance ($(\alpha_1 + \gamma_1) < 0$).

Campbell and Hentschel (1992) estimate a GQARCH(1, 1)-M model and a restricted version of the GQARCH(1, 2)-M model for monthly and daily U.S. stock returns respectively, for the period January 2, 1926 to December 30, 1988. Two sub-samples are also estimated: January 2, 1926 to December 31, 1951 and January 2, 1952 to December 30, 1988. The model for the monthly excess returns, y_{t+1} is given by:

$$y_{t+1} = \mu + \gamma h_t + \kappa\eta_{d,\,t+1} - \lambda_f(\eta^2_{d,\,t+1} - h_t) \tag{2.3.8}$$

$$h_t = \omega + \alpha(\eta_{d,\,t} - b_a)^2 + \beta h_{t-1} \tag{2.3.9}$$

where $\kappa = 1 + 2\lambda_f b_a$, h_t is the conditional variance of y_{t+1}, γ is the coefficient of relative risk aversion, $\eta_{d,\,t+1}$ is the news about dividends, λ_f is the volatility feedback effect, α measures the extent to which a squared return today feeds through into future volatility and b_a governs the predictive asymmetry in the model. The volatility feedback effect is the tendency that an unusually large realisation of dividend news, of either sign, will increase future expected volatility, which in turn lowers the stock price. This will tend to dampen the positive impact of a large piece of good news, while it will magnify the negative impact of a large piece of bad news. Small pieces of news, on the other hand, will lower future expected volatility and increase the stock price. The daily excess returns model is given by:

$$y_{t+1} = \mu + \gamma h_t + \kappa \eta_{d,\, t+1} - \lambda_f(\eta^2_{d,\, t+1} - h_t) \tag{2.3.8}$$

$$h_t = \omega + \alpha_1(\eta_{d,\, t} - b_a)^2 + \alpha_2(\eta^2_{d,\, t-1} - b_a)^2 + \beta h_{t-1} \tag{2.3.10}$$

The coefficient λ_f is found to be highly significant. In the monthly data it is six standard errors from zero, and in the daily data it is almost ten standard errors from zero. Campbell and Hentschel show that the GQARCH model fits the data significantly better when the volatility feedback effect is included. This improvement is due to the fact that the feedback effect can produce excess kurtosis which is in keeping with the excess kurtosis found in most financial time series. For the monthly data, both excess skewness and kurtosis are reduced by approximately one half. The daily data show smaller drops for the skewness and especially the kurtosis, nevertheless, the reductions are significant. The value of b_a is positive and significant, therefore, there is a significant leverage effect. The volatility feedback effect is also in keeping with the fact that stock returns and the conditional volatility of stock returns are negatively correlated. The expected return on a stock is assumed to be a linear function of the conditional variance of the news about dividends. The coefficient of relative risk aversion, γ, is found to be positive but insignificantly different from zero for the full sample, while in the postwar period the γ estimates are sometimes negative but again insignificantly different from zero. Likelihood ratio tests do not reject a model imposing $\gamma = 0$ against the alternative of a free γ with $\lambda_f = 0$. Overall, the study shows no conclusive evidence on the sign of the coefficient of relative risk aversion. In contrast, French, Schwert and Stambaugh (1987) and Chou (1988) find significantly positive relationships between expected returns and the conditional variance.

Sentana (1995) finds that the restricted GQARCH(1, 2)-M model of Campbell and Hentschel (1992) for the conditional variance of daily excess returns can be improved upon by using an unrestricted GQARCH(1, 2)-M model. Equation (2.3.10) can be written as:

$$h_t = \omega + a_{11}(\epsilon_{t-1} - b_a)^2 + a_{22}(\epsilon_{t-2} - b_a)^2 + \beta_1 h_{t-1} \qquad (2.3.11)$$

Sentana shows that this is simply a restricted version of the following model:

$$h_t = \omega + \psi_1\epsilon_{t-1} + \psi_2\epsilon_{t-2} + a_{11}\epsilon_{t-1}^2 + a_{22}\epsilon_{t-2}^2 + 2a_{12}\epsilon_{t-1}\epsilon_{t-2} + \beta_1 h_{t-1} \qquad (2.3.12)$$

The restrictions applied are $a_{12} = 0$ and $\psi_2/a_{22} = \psi_1/a_{11}$. Restricting the cross-product terms to zero can reduce the explanatory power of the model as they take account of the effect of the interaction of the lagged residuals on the conditional variance. Using a robust LM test, Sentana is able to reject the restricted model in favour of the unrestricted model. An even more general model is required to model daily excess returns. The GQARCH(1, 3) model is given by:

$$r_t = \mu + \epsilon_t$$

$$h_t = \omega + \psi_1\epsilon_{t-1} + \psi_2\epsilon_{t-2} + \psi_3\epsilon_{t-3} + a_{11}\epsilon_{t-1}^2 + a_{22}\epsilon_{t-2}^2 + 2a_{12}\epsilon_{t-1}\epsilon_{t-2} + 2a_{23}\epsilon_{t-2}\epsilon_{t-3} + 2a_{13}\epsilon_{t-1}\epsilon_{t-3} + \beta_1 h_{t-1} \qquad (2.3.13)$$

The results show that the level of volatility persistence as given by $a_{11} + a_{22} + \delta_1$ is 0.99389, which is close to but significantly less than one. This equates to a half-life of approximately six months which is consistent with the Campbell and Hentschel results. Sentana finds that the effect of the cross product terms are insignificant after one lag. The leverage effect is similarly short lived, it only being significant for two lags. In contrast, the ARCH effect is more durable. Accordingly, the ranking of the effects is that the ARCH effect is the most important, followed by the leverage effect and finally the cross product terms.

Bekaert and Wu (1997) examine the negative correlation between stock returns and the conditional volatility of stock returns. They put forward two potential explanations of asymmetric volatility: leverage effects and time-varying risk premiums. It has been widely shown that the leverage effect cannot account for all the changes in stock volatility over time. Black (1976) concludes that leverage is probably not the only explanation for the negative relation between stock returns and volatility. French, Schwert and Stambaugh (1987) also conclude that the magnitude of the negative relation between contemporaneous returns and changes in volatility is too large to be attributed solely to the effects of leverage. Schwert (1989) finds that changing leverage explains a small proportion of the increase in stock volatility in the early 1930's and mid 1970's. At best the leverage effect is only able to explain 19.4 percent of the variation in the standard deviation of stock returns.

Bekaert and Wu state that the time-varying risk premium theory involves changes in conditional volatility being caused by return shocks, that is, it is a volatility feedback effect. The volatility feedback effect requires volatility to be persistent; there must also be a positive relationship between the expected return and conditional variance. As mentioned earlier, an increased level of volatility then raises expected returns and lowers current stock prices, dampening volatility in the case of good news and increasing volatility in the case of bad news. The validity of this theory may be brought into doubt by the studies of Glosten et al. (1993) and Nelson (1991) which find a negative intertemporal relationship between expected return and conditional volatility. Against this, Campbell and Hentschel (1992), who formulated the volatility feedback model, find a positive relationship.

To test the aforementioned explanations of asymmetric volatility, Bekaert and Wu use daily observations on the prices and market capitalisation of the firms in the NIKKEI 225 index, together with biannual data on the book value of debt. The sampling period is from January 1, 1985 to June 20, 1994. The data is used to construct three portfolios of five stocks each, representing low leverage, medium leverage and high leverage portfolios. Weekly observations on leverage and stock returns are then extracted from the daily data. The estimated model is given by:

$$\Sigma_t = \Omega\Omega' + B\Sigma_{t-1}B' + C\epsilon_{t-1}\epsilon_{t-1}'C' + D\grave{\eta}'_{t-1}\grave{\eta}_{t-1}'D' + Gl_{t-1}l_{t-1}'G' \quad (2.3.14)$$

where ϵ_t is the unanticipated return, Σ_t is the conditional variance covariance matrix ($\Sigma_t = E(\epsilon_t\epsilon_t' \mid \Psi_{t-1})$), Ψ_{t-1} is the information available, l_t represents the leverage ratios and $\grave{\eta}_t$ is an asymmetric shock where $\grave{\eta}_{it} = -\epsilon_{it}$ if ϵ_{it} is negative and zero otherwise. The asymmetric shocks can capture both a volatility feedback effect and the leverage effect. Ω, B, C and D are n + 1 by n + 1 constant matrices.

Using the above equation system they find that interaction effects between the volatility feedback and leverage effects are important, this makes it hard to isolate their individual effects. Conditional volatility is quite persistent both at the market level and at the portfolio level. The coefficient on lagged volatility is always significant and between 0.3701 and 0.8880, which gives a half-life of between three and a half days and nearly six weeks for the weekly data. The high and medium leverage portfolios exhibit pronounced asymmetry with the low leverage portfolio showing less significant asymmetry. The leverage variables are found to be statistically important in the conditional variance equations, especially for the low leverage portfolio, although their effect on volatility is small compared to the asymmetry generated through the shocks in the GARCH specification. Overall, they find that the volatility feedback effect seems to be the dominant factor behind volatility asymmetry.

2.3.2 Volatility Component Models

Engle and Lee (1993) use two daily stock market indices to estimate the model given by equations (2.2.21) and (2.2.22): the S & P 500 index for the period January 1941 to January 1991 and the NIKKEI index for the period January 1971 to September 1991. The daily stock returns are extracted by taking the log difference of two consecutive trading days' stock prices. The empirical results support the component model. The model successfully captures the typical serial correlation in the squared residuals. The results also show that the permanent component has a higher level of persistence than the temporary component. This shows that deviations of the conditional variance from its trend are stationary.

The results of the asymmetric component model show that negative shocks predict higher volatility than positive shocks with the 'leverage effect' being only a temporary phenomenon of the volatility process. The component model is shown to be successful in correcting the asymmetry of stock return volatility in response to past market shocks when leverage terms are introduced into the model.

Müller et al. estimate the HARCH model for a number of exchange rates over the period January 5, 1987 to January 2, 1994 using a half-hourly business time scale. The HARCH model is able to provide direct information about the structure of the market components. They find that the short term volatility components have the strongest impact with the component over the interval of four to twenty-four hours generally having the weakest impact. This is consistent with actual trading patterns, short term traders only look at high frequency data, thereby giving them the largest impact. Intervals of around twelve hours have little relevance to either short or medium term traders. This is because medium term traders are only interested in longer time intervals and short term traders do not undertake overnight positions. The relevance of the HARCH process to foreign exchange rates is further confirmed by the use of a simulation study. The HARCH process is able to reproduce the asymmetric lagged correlation of the foreign exchange rates, unlike the GARCH process which is not able to do so.

2.3.3 Volatility Persistence

In empirical investigations of high frequency data, a high degree of persistence is regularly found when estimating the conditional variance functions. For example, Baillie and Bollerslev (1989) estimate GARCH(1, 1) models for six daily U.S. exchange rates, they find estimates of $\alpha_1 + \beta_1$ ranging between 0.94 and 0.99, giving a half-life between two weeks and three months respectively. Also, a number of studies have been unable to reject the null hypothesis of a unit root in the autoregressive polynomial, for example, French, Schwert and Stambaugh (1987) found a unit root in the variance of the S & P daily index, and Chou (1988) found one in the variance of U.S. stocks.

Campbell and Hentschel (1992) estimate GQARCH-M models of daily and monthly returns for U.S. stocks over the period January 2, 1926 to December 30, 1988. They find that the level of volatility persistence is distinctly different between the daily and the monthly data. The half-life of a shock is twelve months for the monthly data and six months for the daily data. This is in contrast to Poterba and Summers (1986) who find that the half-life of volatility shocks is just over two months. Campbell and Hentschel attribute this difference to Poterba and Summers' use of an ARIMA model for a moving average of squared daily returns.

Glosten, Jagannathan and Runkle (1993) find that the level of persistence in the conditional variance is dramatically lower when they modify the GARCH(1, 1)-M model by adding terms to take account of asymmetry, the effect of the risk-free interest rate and deterministic seasonals. The first order autoregressive coefficient for h_t is reduced to 0.374 as compared to 0.897 for the GARCH(1, 1)-M model; this equates to a half-life of three weeks and six months respectively. Glosten et al. speculate that the low level of persistence is due to regimes in which variance is relatively persistent, but where there are frequent and relatively unpredictable regime shifts.

Lamoureux and Lastrapes (1990) argue that large persistence may actually represent misspecification of the variance as a result of structural changes in the unconditional variance of the process, as represented by changes in ω in equation (2.2.6). Discrete changes in the unconditional variance of the process produce clustering of large and small deviations which can show up as persistence in a fitted ARCH model. To prove this, Lamoureux and Lastrapes estimate GARCH (1, 1) models holding ω constant and allowing ω to discretely change over sub-periods by introducing dummy variables for deterministic shifts in the unconditional variance. The data is for the daily returns of thirty randomly selected companies over a period of seventeen years. When ω is held constant, the average estimate of $\alpha_1 + \beta_1$ is 0.978 (a half-life of six weeks), as compared to 0.817 (a half-life of just over three days) when ω is allowed to change.

Conrad, Gultekin and Kaul (1990) look at the asymmetry in the predictability of large versus small firms. They use weekly data to estimate GARCH(1, 1)-M models for the returns of three value-weighted portfolios of the one hundred smallest, one hundred intermediate and one hundred largest stocks on the New York and American stock exchanges for the period July 1962 to December 1988. They find that the half-life of volatility shocks varies dramatically across the portfolios. The shocks to the smallest firms have a half-life of nearly seven weeks, as compared to five months for the intermediate firms and over two years for the largest firms. They also find that shocks to large firms are important for the behaviour of the returns of smaller firms as well as their own returns. Against this, they find that shocks to smaller firms had little relevance for the behaviour of the returns of larger firms. As a consequence, they stated that any model of the time-varying moments of stock returns needs to take into account these asymmetric effects.

2.3.4 Autocorrelation in the Conditional Mean

A number of studies find that stock and index returns are positively autocorrelated. Various theories such as non-synchronous trading, transaction costs, time-varying expected returns and feedback trading have been put forward to explain this phenomenon. The non-synchronous trading hypothesis is put forward by Fischer (1966) and Scholes and Williams (1977). The positive index return autocorrelation is induced by positive cross-autocorrelations between individual stocks. These arise because some stock prices do not incorporate the latest information as they are traded less frequently than others. The time-varying expected returns theory attributes the returns autocorrelation to systematically varying risk premia. Cohen et al. (1980), Mech (1993) and Ogden (1997) contend that market makers base their quotes only on a limited set of information due to the transactions costs involved in obtaining full information. This results in autocorrelation in the index due to the inefficient quotes that market makers give. Finally, feedback trading incorporates a number of trading strategies which are guided by price movements, such as stop-loss orders, value trading, momentum trading and profit taking. Positive feedback trading involves investors buying after price rises (momentum trading), while negative feedback trading results in investors selling after price rises (profit taking). Positive feedback trading results in negative return autocorrelation while negative feedback trading results in positive return autocorrelation.

Säfvenblad (2000) examines daily returns for 62 major stocks traded on the Stockholm Stock Exchange over the period 1980 to 1995 using the following equation:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \qquad (2.3.15)$$

Säfvenblad finds that Swedish index returns are strongly positively correlated. The index has a return autocorrelation of 0.345 while the individual stocks have an average return autocorrelation of 0.110. Overall, he finds that non-synchronous trading and transactions costs add to the observed level of index return autocorrelation but cannot explain the autocorrelation properties of individual stock returns. The observed patterns of autocorrelation can more readily be explained by a feedback trading model.

Säfvenblad (1997) looks at daily returns for the 70 most traded stocks on the Paris Bourse over the period 1991 to 1995. He finds a stock return autocorrelation of 0.07. He concludes that index return autocorrelation is consistent with efficient markets and prices. The absence of market imperfections such as transaction costs and measurement errors need not result in the level of autocorrelation being zero. Other studies also find positive and significant values for the return autocorrelation. Ronen (1998) examines fifteen stocks on the Tel Aviv stock exchange for the period May 1987 to November 1990, the stock return autocorrelation is found to be 0.12. Generally, the level of stock return autocorrelation is found to be smaller for U.S. listed stocks. Atchison, Butler and Simonds (1987) find an insignificant level of stock return autocorrelation of 0.02 for the CRSP stock series. Chan (1993) looked at NYSE stocks and found a significant stock return autocorrelation level of 0.09.

2.3.5 Monday Effect

It is well known that the distribution of stock returns depends on the day of the week, with the lowest mean returns occurring on a Monday. For example, Cross (1973) examines daily price movements of the S & P 500 index over the period January 1953 to December 1970. He finds that the mean return on a Friday is 0.12% as compared with -0.18% on a Monday. He states that the probability of such a large difference occurring by chance is less than one in a million. French (1980) looks at daily stock returns on the S & P 500 for the period January 1953 to December 1977. He reports that returns tend to be negative from Friday's close to Monday's close and that this is not simply the result of the longer three-day period between the closing prices. Gibbons and Hess (1981) find that Monday's return is significantly lower than for other days when they examine daily movements for the S & P 500, CRSP value weighted and equally weighted portfolios over the period July 1962 to December 1978. As market traders show no systematic variations in their consumption preferences over the course of the week, there seems to be no economic justification for the variation in returns. This could imply the rejection of the notion of market efficiency due to the possibility of trading rules generating predictable economic profits. The ability to exploit these predictable events, and thereby generate profits, depends on the level of market liquidity and interrelated transaction costs. A number of explanations have been put forward for the strong Monday effect. For example, delays between trading and settlement in stocks (Gibbons and Hess (1981) and Lakonishok and Levi (1982)), measurement error (Keim and Stambaugh (1984)), institutional factors (Thaler (1987)) and trading patterns (Lakonishok and Maberly (1990)). Unfortunately, individually they offer no significant explanation for the Monday effect. Even taken as a whole, they appear to explain only a small portion of the Monday effect.

Sullivan et al. (1998) attribute the significance of the Monday effect to data snooping. Data snooping occurs because economic studies typically use non-experimental data, thus it is not possible to generate new data sets to test hypotheses independently of the data that led to the theory. This practice can lead to serious biases in statistical inference as in the limited sample sizes used in economic studies, systematic patterns and seemingly significant relations are bound to occur if the data is analysed with sufficient intensity. Stock return data is particularly susceptible to data snooping due to the importance of outliers in the returns series, by chance a model that outperforms a benchmark series will be found if enough models are studied.

Sullivan et al. examine Dow Jones Industrial Average daily data for the period January 1897 to May 1986, together with an out-of-sample period for June 1986 to December 1996. They consider all possible combinations of the rules being long (short) while being neutral otherwise and neutral while being long (short) otherwise for each of the calendar effects under consideration. The calendar effects are day of the week, week of the month, month of the year, semi-month, holidays, end of December and finally turn of the month. Combinations of up to two of the frequencies are considered, such as day of the month effects. Overall, this yields a total of 9,452 rules. They find that the best rule for the period up to May 1986 is the Monday rule (neutral on Monday, long otherwise). When allowance is made for data snooping by analysing the Monday effect in the context of all the possible rules that could be chosen, they find that the Monday rule does not produce a significantly better performance than the market index. This is confirmed by the Monday rule leading to lower returns than the index for the out-of-sample data. Additionally, they analyse the Monday effect from its initial date of publicity in Cross (1973) through to 1996, revealing that it did not continue to significantly outperform.

Sullivan et al. also examine the Cross (1973), French (1980) and Gibbon and Hess (1981) sample periods when considered in conjunction with twenty day of the week rules. They find that the Monday effect is bordering on statistical insignificance for the first two samples and insignificant for the Gibbon and Hess sample. They conclude that evaluating the Monday effect in the context of core day of the week rules renders the statistical significance of the Monday effect doubtful, even in the period during which the Monday effect is discovered. Additionally, allowing for data snooping, no calendar rule appears to be capable of outperforming the benchmark index.

2.4 Conclusions

The ARCH model of Engle (1982) is the first formal model that emerged for characterising time varying variances. It captures the phenomenon of volatility clustering and it has an unconditional distribution for the error which displays kurtosis. Against this, it is also computationally burdensome when a large number of lags are required. The generalised-ARCH (GARCH) model of Bollerslev (1986) solves this problem. Although, in common with the ARCH model, it does not adequately account for the kurtosis found in many financial time series. Nevertheless, the GARCH model captures the basic features of financial data. Therefore, I will utilise it to model the daily prices of forty-five FTSE 100 companies over the period 4/1/1988 to 7/9/98. It is likely that the linearity assumption of GARCH models will restrict their suitability for the financial time series that I intend to model.

A number of nonlinear exponential models have been proposed. The exponential GARCH (EGARCH) model of Nelson (1991) was the first to capture the asymmetric response of volatility to past shocks. This has been followed by the threshold-GARCH model of Glosten, Jagannathan and Runkle (1993) and the quadratic ARCH (QARCH) model of Sentana (1995). These models more adequately account for the excess kurtosis found in financial time series. The EGARCH and QARCH models have the benefit that they can also be used to measure the volatility feedback effect. In my initial investigations of volatility asymmetry, I will concentrate on the use of

TGARCH models. This will allow me to verify the superior ability of this model to explain the daily price movements of the companies that I intend to examine.

A remaining problem of the above models is that they tend to give distinctly different levels of volatility persistence for high frequency as opposed to lower frequency data. The persistence of high frequency volatility shocks tends to be measured in hours as compared to months for the lower frequency data. This paradox can be resolved by the use of volatility component models. Andersen and Bollerslev (1996) proposed that volatility components arise as a result of heterogeneous information processes. Similarly, Müller et al. (1997) proposed that they result from the actions of heterogeneous traders. An empirically easier model to investigate is the unobserved component model of Engle and Lee (1993). In this model the conditional variance is decomposed into permanent and transitory components which help to explain the long-run and short-run movements of stock market volatility. Initially, I will use the Engle and Lee model to examine the daily data in common with the other models. The use of higher frequency data could also give a clearer picture of the underlying volatility components.

A number of papers have examined the link between volatility persistence in individual stock returns and the rate of information arrival. The MDH model of Clark (1973) suggests that trading volume, which acts as a proxy for the rate of information arrival, can explain the volatility persistence of stock returns. If this holds, ARCH would simply be a manifestation of the daily time dependence in the rate of information arrival to the market for individual stocks.

Chapter 3 - Modelling Methodology and GARCH type Modelling Results

3.1 Data

The sample of stocks is selected on the basis that they must be continuous members of the FTSE 100 index from 4/1/1988 to 7/9/98. This eliminates companies that have either been taken over or that have been dropped due to poor relative performance. This leaves a data set containing the daily stock prices of forty-five FTSE 100 companies. The daily values of the FTSE 100 index are also used as a comparison measure. The source of the data is DATASTREAM. The daily returns are calculated by using $r_t = \log(p_t/p_{t-1})$, where p_t is the stock price at time t. This gives 2,785 observation points. Summary statistics for the returns data are shown in Table 3.1. The returns exhibit excess kurtosis, thereby leading to a significant Jarque-Bera test statistic and the rejection of the null hypothesis of normality.

3.2 Estimation Procedure

The initial conditional mean model under consideration is of the autoregressive, AR(1) model:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{3.2.1}$$

The Monday effect is examined by modifying the conditional mean equation via the inclusion of a dummy variable term M_t, such that $M_t = 1$ when the day of the week is Monday and zero otherwise. The conditional mean equation becomes:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t \tag{3.2.2}$$

The conditional mean equation (3.2.1) is also revised to allow the conditional mean to be an explicit function, in part, of the conditional variance process by using the GARCH-M model. The conditional mean model is given by:

$$r_t = \mu + a_1 r_{t-1} + \gamma h_t + \epsilon_t \tag{3.2.3}$$

where γ may be interpreted as the coefficient of relative risk aversion. The above models are estimated jointly with a number of conditional variance models. Estimation of all the conditional variance models is performed by maximum likelihood using iterative nonlinear methods under the assumption that disturbances are normally distributed, $\epsilon_t \mid \Psi_{t-1} \sim N(0, h_t)$. However, on an empirical basis, the assumption of conditional normality cannot generally be supported as the leptokurtosis generated by GARCH models is insufficient to capture that in the data, such that the standardised residuals exhibit excess kurtosis. Alternatives to the conditional normal distribution such as the conditional t distribution and the Generalised Error Distribution (GED) have been used. They are symmetric distributions that allow the kurtosis to be different from that of the normal distribution. The conditional t distribution allows for heavier tails than the normal distribution and includes the normal distribution as a limiting case. The GED incorporates distributions with tails both thicker and thinner than the normal distribution, also including the normal distribution as a special case. Nevertheless, dealing with the problem of conditional kurtosis is still possible while maintaining the assumption of conditional normality. This is achieved by using quasi-maximum likelihood (QML) estimation that gives consistent estimates, together with computing robust standard errors using the consistent variance-covariance estimator of Bollerslev and Wooldridge (1992).

Model orders are determined by the Schwarz criterion together with the examination of residual diagnostics. Signs of mean and variance misspecification are provided by Ljung-Box statistics for serial dependence in the levels and the squares of the standardised residuals respectively. A further test of variance misspecification is provided by the ARCH-LM test of Engle (1982).

3.3 Test Methods

3.3.1 Jarque-Bera Test Statistic

The Jarque-Bera is a test statistic for examining the null hypothesis of whether a residual series is normally distributed. It compares the skewness and kurtosis of the series to that of the normal distribution. The statistic is computed as:

$$JB = \frac{T - k}{6}\left(S^2 + \frac{1}{4}(K - 3)^2\right) \tag{3.3.1}$$

where S is the skewness, K is the kurtosis, k represents the number of estimated parameters used to generate the residual series and T is the number of observations in the series. The statistic is distributed as χ^2 with two degrees of freedom.

3.3.2 Wald Test Statistic

The Wald test examines restrictions on the coefficients of the explanatory variables of a model. The test statistic is computed by estimating an unrestricted regression without imposing the coefficient restrictions specified by the null hypothesis. The Wald statistic measures how close the unrestricted estimates come to satisfying the restrictions under the null hypothesis. If the restrictions are valid, the unrestricted estimates should come close to satisfying the restrictions.

The Wald statistic is computed as:

$$W = \frac{RSS_r - RSS_u}{RSS_u/(T - k)} \tag{3.3.2}$$

where RSS_r and RSS_u are the residual sum of the squares from the restricted and unrestricted regressions respectively. Under the null hypothesis that the restrictions are valid, the Wald statistic has an asymptotic $\chi^2(q)$ distribution, where q is the number of restrictions.

3.3.3 Schwarz Criterion

The Schwarz criterion is used as an overall performance measure; it strikes a balance between the measure of goodness of fit and the parsimonious specification of the model. This is accomplished by using a penalty for the number of model parameters. Consequently, an additional parameter will only be included in the model if it sufficiently adds to the explanatory power of the model, thereby reducing the value of the selection criterion. It tends to favour models with fewer parameters than may be optimal because it imposes a relatively large penalty for additional coefficients. The Schwarz criterion is given by:

$$SC = \frac{-2l}{T} + \frac{k\log T}{T} \tag{3.3.3}$$

where l is the value of the log likelihood function using the k estimated parameters.

3.3.4 Ljung-Box Statistics

The Ljung-box Q-statistics are used to test for remaining serial correlation in the mean equation and to check the specification of the mean equation. Likewise, the Q^2-statistics are used to test for remaining ARCH in the variance equation and to check the specification of the variance equation. If the mean and variance equations are correctly specified, all the Q^2-statistics should be insignificant. The Q-statistic at lag i is a test statistic for the null hypothesis that there is no autocorrelation up to order i and is computed as:

$$Q_{LB} = T(T+2)\sum_{j=1}^{i}\frac{r_j^2}{T-j} \tag{3.3.4}$$

where r_j^2 is the j-th autocorrelation of the residuals and T is the number of observations. Similarly, the Q^2-statistic at lag i is given by:

$$Q_{LB}^2 = T(T+2)\sum_{j=1}^{i}\frac{r_j^2}{T-j} \tag{3.3.5}$$

It is a test statistic for the null that there is no ARCH in the residuals up to order i, where r_j^2 now represents the j-th autocorrelation of the squared residuals. When the residuals are from ARMA estimation, the Q and Q^2 statistics are distributed as χ^2 with degrees of freedom adjusted to represent the number of autocorrelations less the number of AR and MA terms previously estimated.

3.3.5 ARCH-LM Test

The ARCH-LM test of Engle (1982) is a Lagrange multiplier (LM) test for ARCH in the residuals. The ARCH-LM test statistic examines the null hypothesis that there is no ARCH up to order i in the residuals. The following auxiliary test regression is run:

$$\epsilon_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \alpha_2\epsilon_{t-2}^2 + \ldots + \alpha_i\epsilon_{t-i}^2 + \nu_t \tag{3.3.6}$$

where the ϵ_t's are the residuals from the ARMA(m, n) conditional mean equation. The test statistic is computed as TR^2, where T is the number of observations and R^2 is the coefficient of determination from the above regression of the squared residuals on a constant and lagged squared residuals up to order i. Under the null hypothesis, the LM test statistic is asymptotically distributed as χ_q^2.

3.4 GARCH /GJR Model Results

The AR(1)-GARCH/GJR(p, q) model estimates for the thirty-nine FTSE 100 companies[1], and the index itself, are reported in Table 3.2. Thirty companies have non-significant values for the dummy variable term, as a result, the GJR model reduces down to the GARCH model for these companies. Consequently, the GARCH model estimates are reported for these companies. The parameter estimates show that only the coefficients for Reckitt & Colman do not satisfy the conditions as outlined by Nelson and Cao (1992) for a positive conditional variance in all circumstances. Against this, the in-sample conditional standard deviation for Reckitt & Colman always remains positive as seen in figure 3.1. Therefore, the failure to satisfy the positive conditional variance conditions only affects out of sample measurements. Excluding the constant terms, all the coefficients are significant at the 5 per cent significance level. The positive values of the ARCH(1) and GARCH(1) coefficients show that volatility is positively related to shocks

[1] The estimation results for six companies are not included due to serial correlation problems in the mean equation. This remained the case even after controlling for leverage effects, transitory and permanent volatility components, short-run leverage effects, volatility spikes and the Monday effect. The source of the remaining residual structure could not be found, consequently, the correctly specified models could not be identified.

to the conditional mean and to previous volatility levels. The estimated level of volatility persistence is found to be very high for most of the firms. As can be seen from Table 3.3, the volatility half-life is generally more than twenty days. The volatility persistence level is higher than 0.90 for thirty-nine companies and higher than 0.95 for thirty-six of the companies examined. As a consequence, the limiting IGARCH case cannot be ruled out for twenty-one of the companies due to the failure to reject the restriction $\lambda = 1$ using a Wald test. Therefore, shocks to the conditional mean process would persist indefinitely in conditioning the future conditional variance for these companies.

All the stock return autocorrelations are found to be positive and are generally significant at the 5 percent level. The results are consistent with negative feedback trading strategies such as value trading (buying after price falls) and profit taking. The return autocorrelation varies from 0.0144 for Asda to 0.1654 for Reuters with the index return autocorrelation being 0.0734. This is similar to the levels of return autocorrelation found in other studies. The asymmetric volatility estimates confirm significant asymmetry whereby negative shocks increase volatility by a greater magnitude than positive shocks of an equal size, in accordance with the hypothesised leverage effect discussed in chapter 2. The estimates show that a negative shock raises conditional variance by between 2.3 percent (British Airways) and 5.8 percent (Ladbroke) in comparison with an equivalent positive shock.

Residual diagnostics for the AR(1)-GARCH/GJR(p, q) models are reported in Table 3.4. The Jarque-Bera statistics indicate residual non-normality due to the excess kurtosis of the residuals. This points to the correct use of Bollerslev-Wooldridge robust standard errors. The Ljung-Box statistics indicate some serial dependence in the levels with no serial dependence in the squares of the standardised residuals. The ARCH-LM test also shows no variance misspecification. At the five percent significance level, the Q_5 statistic for Prudential and Reuters is significant. The Q_{10} statistic is significant at the five percent level for BAT Industries, Bass, Boots, Diageo, General Electric, Marks & Spencer, Natwest Bank, and Prudential. In all these cases the lag length is relatively long which leads to the possibility of spurious results.

3.5 GARCH-M Model Results

All of the companies have insignificant GARCH-M terms, therefore, they reduce down to the estimated standard GARCH/GJR models previously reported. As a result of the limited relevance of the conditional mean specification (3.2.3), as used in the GARCH-M model, no other conditional variance specifications are estimated using this mean specification.

3.6 CGARCH/ACGARCH Model Results

CGARCH/ACGARCH model estimates for thirty-four FTSE 100 companies are reported in Table 3.5. The remaining five companies and the FTSE 100 index have non-significant transitory component parameters and, as a result they reduce down to the GARCH/GJR models reported earlier. Six companies have significant dummy variable terms for transitory asymmetry. The remaining companies have non-significant coefficients for the dummy variable term, therefore, they reduce down to the CGARCH model. The values of the stock return autocorrelations are all significantly positive and are comparable to the previous results. Estimates of the autoregressive root in the permanent component are significant for all the companies, and higher than 0.95 for all the companies and higher than 0.99 for twenty-three companies. Indeed, Table

3.6 shows that the null hypothesis of integration in the permanent component can be rejected on the basis of a Wald test at the 5 percent significance level for only ten companies. Overall, the level of persistence is marginally higher for the volatility component models as compared with the GARCH models examined earlier. Also, there is no significant time-variation in the permanent component for Glaxo Wellcome and Land Securities. The two companies have integrated permanent components, therefore, their permanent components can be characterised as random walks.

The shock to the transitory component is significant for thirty of the companies. Generally, the impact of a shock to the transitory component is two to three times larger than the impact of a shock to the permanent component. Against this, the half-life of a shock to the transitory component is typically less than three days, whereas the half-life of a shock to the permanent component is generally greater than fifty days.

A number of the companies fail to satisfy the conditions for non-negativity of the conditional variance in all circumstances. The companies that fail the conditions are Enterprise Oil, General Electric, Marks & Spencer, Rank Group, Reckitt & Colman, Reed International and Sainsbury. However, as seen from figures 3.2 to 3.8, the conditional standard deviation remains positive at all times for all of the companies. As a result, the failure to pass the non-negativity conditions will only affect out of sample measurements. The covariance stationarity conditions are satisfied for all the companies examined.

The results indicate that Barclays, British Airways, CGU and General Electric all have negative shocks that increase volatility by a greater magnitude than positive shocks of an equal size. Referring to the final column of Table 3.6, Wald tests also indicate that the initial impact of bad news for these companies is significant. Boots and Cadbury Schweppes have estimates that imply that negative shocks reduce volatility as compared to positive shocks of an equal size. Nevertheless, Wald tests indicate that the initial impact of bad news for these companies is insignificant at the five percent significance level. Therefore, the results represent strong support for the existence of a temporary 'leverage effect'. The estimates show that a negative shock raises conditional variance by between 7.0 percent (CGU) to 16.8 percent (British Airways) in comparison with an equivalent positive shock. With the exception of General Electric, the companies that support the leverage effect have insignificant values of α. This indicates that negative shocks dominate the effects on the transitory component of volatility with the effect of positive shocks being generally insignificant. For General Electric, both good and bad news have an equal but opposite impact on transitory volatility, that is, good news reduces transitory volatility as much as bad news increases transitory volatility. Of the four companies that support a temporary 'leverage effect', the GJR model only detected a 'leverage effect' for British Airways. Therefore, the ability to detect a temporary 'leverage effect' represents a substantial improvement over the GJR model.

Residual diagnostics for the volatility component models are reported in Table 3.7. The levels of skewness and kurtosis are similar to those of the GARCH models. The Jarque-Bera test statistics continue to reject the null hypothesis of normality, showing the correct use of robust standard errors. The Ljung-Box statistics for the volatility component models are comparable to those of the GARCH models with only a slight improvement. The statistics indicate some serial dependence in the levels and no serial dependence in the squares of the standardised residuals. At the 5 percent significance level, the Q_5 statistics for Prudential and Reuters are significant together with the Q_{10} statistic for Bass, Boots, Cadbury Schweppes, Diageo, General Electric, Marks & Spencer, Prudential and Standard Chartered. The relatively long lag length leads to the possibility of spurious results. The ARCH-LM test shows no variance misspecification at the 5 percent significance level.

Overall, in terms of characterising the volatility, the CGARCH/ACGARCH model represents an improvement over the GARCH/GJR model. The transitory component parameters are only insignificant for five of the companies examined, these cases reducing to GARCH models. The component model also tends to have higher values of volatility shock half-lives. The possible underestimation of volatility shock half-lives by the GARCH model could lead to poorer volatility forecasts. The permanent-transitory decomposition also leads to improvements in estimation when applied to a model of non-linear conditional variance. The ACGARCH model identifies five companies with transitory asymmetric volatility for which the GJR model did not find any asymmetric volatility. Overall, the GJR and ACGARCH models identify fourteen companies together with the index having some measure of asymmetric volatility. There are a number of possible reasons for the widespread existence of the 'leverage effect'. The asymmetric volatility evident in the index could result from the asymmetric volatility found in a number of its constituent companies. Likewise, the causality of the asymmetric volatility could also run from market wide 'leverage effects' inducing asymmetric volatility in the companies. The high proportion of firms with asymmetric volatility could also result from the way the sample is chosen. A sample selection bias could be introduced by only examining firms that stayed in the index between 4/1/1988 to 7/9/1998. Especially for the smaller companies within the index, only the companies whose share price performed relatively well over the sample would be chosen. Also, poorly performing large companies can be taken over and thereby drop out of the index. It is inevitable that, by the way of its construction, the FTSE 100 index will involve 'churning' of the index composition.

3.7 Monday Effect Results

Model estimates for AR(1)-GARCH/GJR(p, q) models including the Monday effect are reported in Table 3.8 for the twenty FTSE 100 companies which have significant Monday effects and the index itself. The Wald test statistics for the null hypothesis that a Monday effect does not exist can be rejected for all twenty-one cases. The results are similar to those of the standard GARCH/GJR models except that the conditional mean return is approximately doubled. This is because the lower return on a Monday is not included. For these companies, the dummy variable terms indicate that the stock return on a Monday is lower by between 0.10 to 0.28 percent.

CGARCH/ACGARCH model estimates for the Monday effect are reported in Table 3.9. Sixteen of the twenty-one cases identified by the GARCH model have significant component model terms, the remaining five cases reduce down to the Monday effect GARCH/GJR model as they have transitory volatility component terms which are insignificant. Once again, the remaining estimates are similar to those of the standard volatility component except that the conditional mean return is approximately doubled. Taking into account volatility components leads to Enterprise Oil and Rio Tinto having insignificant Monday effect terms. Cadbury Schweppes has an insignificant Monday effect term as a consequence of allowing for short-run leverage effects, with the remaining companies all having significant Monday effect terms. The short-run leverage effect for CGU is insignificant at the five percent level as a result of allowing for the Monday effect. Overall, of the twenty-one cases shown to exhibit a Monday effect by the GARCH/GJR model, three have insignificant Monday effect terms when either volatility components or short run leverage effects are taken into account. This leaves eighteen companies with significant Monday effect terms, which can bring in to question the efficiency of the market in these stocks as there is the possibility of profitable trading rules existing. Nevertheless, the results can still be consistent with an efficient market due to transaction costs which leave no profitable opportunities.

3.8 Model Comparisons

Tables 3.10 and 3.11 give the log likelihood and Schwarz criterion values for the GARCH, GJR, CGARCH and ACGARCH models. The Schwarz criterion is more favourable to models with fewer parameters. The GJR model improves on the GARCH model for all ten cases when judged by the Schwarz criterion. This shows that where the coefficient of the GJR model is significant, the asymmetric model representation gives an improvement. In contrast, the CGARCH model improves on the GARCH model for only eleven of the thirty-four companies for the Schwarz criterion. Overall, despite breaking the volatility down into components, the CGARCH model does not sufficiently improve on the GARCH model in terms of modelling ability. The asymmetric component model proves useful in modelling the short-term leverage effect, in that it improves on the component model for all the six companies where it can be used.

3.10 Conclusions

The standard GARCH model can be improved in a number of ways to give a better representation of stock returns for the FTSE 100 series examined. Allowing the conditional mean to be an explicit function of the conditional variance is found to be of no benefit. GARCH models are linear in the conditional variance, therefore, they cannot model phenomenon such as the 'leverage effect', which is the negative correlation between volatility and past returns. This suggests that models of non-linearity in conditional variance with respect to past shocks need to be used. The GJR model incorporates a non-linear conditional variance in a quadratic form. This results in improved modelling ability, when judged by information criteria, for the companies which have significant asymmetry terms. Another area of potential improvement is the permanent-transitory volatility decomposition. This is because the GARCH and GJR models assume homogeneity of the price discovery process and are unable to capture the effects of short and long-run volatility components. Despite more accurately characterising volatility, the CGARCH model does not represent an improvement over the GARCH model in terms of modelling ability. Transitory component parameters are only insignificant for six of the cases examined, these cases reducing to GARCH models. The possible underestimation of volatility shock half-lives by the GARCH model as compared to the volatility component model could lead to poorer volatility forecasts. The ACGARCH model improves upon the CGARCH model for the six companies where its use is valid.

Overall, the GJR and ACGARCH models identify approximately one third of the companies as supporting the 'leverage effect'. Possible reasons for the widespread existence of the 'leverage effect' include asymmetric volatility in the index resulting from the asymmetric volatility found in its constituent companies, market wide 'leverage effects' inducing asymmetric volatility in the companies and 'churning' of the index composition introducing sample specific effects.

All the stock return autocorrelations are found to be positive and are largely significant at the five percent level. The results are consistent with negative feedback trading strategies such as value trading (buying after price falls) and profit taking. The return autocorrelation is found to vary from 0.014 to 0.165 with the index return autocorrelation being approximately 0.073. This is similar to the levels of return autocorrelation found in other studies. This can have implications about the efficiency of the stock market due to the predictable patterns in stock returns. Nevertheless, taking advantage of the predictable return patterns involves an element of risk which can account for the stock return autocorrelation pattern. This is because a certain risk premium would be needed in order to take on the risk.

Twenty-one companies are shown to exhibit a Monday effect by the GARCH model, this allows the possibility of profitable trading rules which can bring in to question the efficiency of the market in these stocks. Three of the companies have insignificant Monday effect terms when more robust checks involving volatility components, leverage effects or short-run leverage effects are taken into account. This leaves eighteen companies with possible efficiency problems, although transaction costs involved in trading can still lead to the results being consistent with an efficient market.

Chapter 4 - Forecasting Methodology and GARCH type Forecasting Results

4.1 Introduction

Stock price volatility has come under increased recent scrutiny because large swings in stock price movements have occurred with greater frequency than the historical average (Schwert, 1990; Robinson, 1994; Antoniou and Holmes, 1995). It is believed that this is due to institutional changes such as program trading and the introduction of derivative futures and options. Consequently, greater recognition has been given to the importance of accurate volatility estimates and forecasts. The forecast of volatility is the most important parameter affecting the price of options. An increased accuracy in forecasting volatility results in a lower probability of making losses on option contracts.

As can be seen from the following literature review, there is no clear consensus as to the superior conditional volatility forecasting model. The optimal volatility forecasting terms model tends not to be the same for different time frequencies. To this end, the forecasting accuracy of the GARCH class models estimated in chapter three will therefore be examined in comparison with a number of benchmark models for daily and four-weekly data . This is important, as in a UK stock market context, only McMillan, Speight and Gwilym (2000) have analysed the volatility forecasting performance of GARCH class models. It would be expected that the GARCH class models will give a relatively poor forecast performance for daily data. This is because the inherent noise in the return generating process will reduce the explanatory power of the GARCH class volatility models. For the four weekly data, the effect of the noise in the return process can be reduced by using daily data to evaluate the true volatility. It would then be expected that the

GARCH class models would give a relatively better forecasting performance against the benchmark models.

The remainder of the chapter is organised as follows. Section two details the empirical evidence relating to the forecasting ability of the GARCH class of models. Section three contains information about the data set and forecast procedure used. Sections four and five describe the volatility forecasting models and the methods used to evaluate forecast performance. Sections six and seven give the forecast results with section eight offering some concluding remarks.

4.2 Literature Review

When estimating GARCH models for speculative returns, a high degree of persistence together with significant parameter estimates are generally found. Consequently, financial market volatility should be highly predictable. In spite of this, most studies find that GARCH class models explain little of the variability in ex-post squared returns. For example, Cumby, Figlewski and Hasbrouk (1993) use weekly excess returns on five broad asset classes to assess the forecasting ability of EGARCH, historical volatility and a forecast based on the squared return from the last period. Their results reveal that all the models do badly, with EGARCH models proving the least biased for the sample forecasts. Jorion (1995) examines the information content and the predictive power of GARCH and moving average models versus implied standard deviations. The GARCH models are outperformed by implied standard deviations, which are themselves biased volatility forecasts. Figlewski (1997) examines monthly returns on the S&P 500 and twenty year Treasury bond yields to perform long-term volatility forecasts (six, twelve and twenty-four months), by using the GARCH(1, 1) model and historical volatility measured over the previous five and ten years. He finds that the two models perform equally well for the S & P 500, but for the Treasury bond yield, the GARCH model appears substantially less accurate than historical volatility, and gets worse the longer the forecast horizon. He also finds that GARCH class models have three shortcomings as forecasting tools. First, they typically need a large number of data points for robust estimation. Second, the models are subject to the problem that the greater the number of parameters involved, the better the in-sample fit but the quicker the model falls apart out-of-sample. Third, the GARCH class models are better suited to one-step ahead forecasts, they are not designed to produce variance forecasts for a long horizon.

Andersen and Bollerslev (1997b) show that there is no contradiction between good volatility forecasts and poor predictive power for the daily squared returns. They state that the approximation of the true volatility by the squared returns introduces a substantial noise. This inflates the estimated forecast error statistics and substantially reduces the explanatory power of GARCH volatility forecasts with respect to the true volatility. Forecast evaluation is usually carried out by comparing the implied predictions of a model with the subsequent actual values. Unfortunately, the latent volatility cannot be directly observed. This necessitates the use of a proxy measure of volatility. It is known that the returns of the conditional mean function can be written as $r_t = Z_t\sqrt{h_t}$. If the model is correctly specified, then $E_{t-1}(r_t^2) = E_{t-1}(Z_t^2 h_t) = h_t$. Therefore, it appears that the squared returns can act as a proxy for ex-post volatility. Nevertheless, although the squared returns act as an unbiased estimator for the latent volatility factor, they can give very noisy measurements due to the idiosyncratic error term, Z_t^2. The error term generally exhibits a high degree of observation by observation variation relative to h_t. This results in the volatility process only contributing to a small amount of the variation in the squared returns. Consequently, when judged by standard forecast evaluation criteria using r_t^2 as a measure for ex-post volatility, the explanatory power of the GARCH class volatility models will be poor due to the inherent noise in the return generating process.

The degree to which the idiosyncratic error term affects the forecasting ability of the volatility model depends on the frequency level at which the true volatility is measured. If the true volatility is measured at the same frequency as the forecasts, Christodoulakis and Satchell (1997) show that even for an unbiased GARCH predictor, the true mean squared error for log volatility will be increased by a factor 6.5486. This is up to three thousand times the size of the true mean squared error. Andersen and Bollerslev (1997b) state that theoretically, as the observation frequency increases from a daily to an infinitesimal interval, the squared return innovations converge to the true measurement of the latent volatility factor. In their empirical investigation, they find that high frequency returns yield a dramatic reduction in noise. They conclude that when evaluated against these improved volatility measurements, daily ARCH models do well, readily explaining about half the variability in the volatility factor.

Similarly, the modelling of monthly and weekly volatility can also be improved by using daily data to evaluate the true volatility instead of monthly data. This is especially the case, as the smaller number of sample points involved gives a relatively large sampling error as compared with the daily data. An increase in the sampling frequency will increase the proportion of the variance of the squared return innovations that is attributable to the volatility process. Nevertheless, while the use of daily data constitutes an improved measure of true volatility, there will still be a significant component of noise left out.

The use of daily returns in calculating monthly ex-post volatility is first put forward by Schwert (1989). He examines American stock returns based on monthly data for 1859 to 1987 and on daily data for 1886 to 1987. He finds that volatility predictions from the daily data are much higher following the 1929 and 1987 stock market crashes because there are very large daily returns in October 1929 and October 1987. Overall, the volatility predictions from the daily data are more in keeping with actual volatility levels. The increased sampling frequency leads to the forecasting ability of the GARCH model being less sensitive to extreme within-sample observations.

Brailsford and Faff (1996) use daily data on an Australian stock index for the period January 1, 1974 to June 30, 1993. A monthly volatility series is generated by taking the sum of the daily squared returns. They compare the predictive performance of a variety of statistical methods with GARCH and threshold GARCH models. They find that no single model is clearly superior. The ranking of the forecast models is dependent on the choice of forecast error statistic. The variability in the rankings highlights the potential dangers of selecting the optimal model on the basis of a subjective choice of error criterion. Brailsford and Faff conclude that while it is difficult to claim superiority of any one model, the GJR-GARCH(1, 1) model is their choice.

McMillan, Speight and Gwilym (2000) are the first to report a volatility forecasting analysis of GARCH models for the UK stock market. They use daily, weekly and monthly data on the FTSE 100 index for the period January 2, 1984 to July 31, 1996, and for the FTA all share index from January 1, 1969 to July 31, 1996. The forecasting performance of GARCH, threshold GARCH and component GARCH models is evaluated against a number of statistical models. In common with Brailsford and Faff (1996), they find that no model is clearly superior; the ranking of the forecast models is dependent on the choice of forecast error statistic and the sampling frequency. For the symmetric loss case, the random walk model is found to provide vastly superior monthly volatility forecasts. Weekly volatility forecasts are moderately superior for the random walk, moving average and recursive smoothing models. While for daily volatility forecasts, GARCH, moving average and exponential smoothing models prove to be marginally better. Overall, when only symmetric loss functions are considered, they find that the most consistent forecasting performance is provided by GARCH and moving average models.

It has been shown that the forecasting performance of the GARCH class of models is sensitive to extreme within-sample observations. This is because extreme in-sample observations in the returns process occur more frequently than would be expected from a normal distribution. Even asymmetric GARCH models typically display excess kurtosis. Franses and Van Dijk (1996) compare the volatility forecasting performance of the GARCH, QGARCH and threshold GARCH models with the random walk model. They examine weekly data on five European stock indices over the period 1986 to 1994. Their results show that when the forecasting models are calibrated on data that exclude such extreme events as the 1987 stock market crash, the QGARCH model can significantly improve on the linear GARCH model and the random walk model. They also find that the GJR model performs poorly and they could not recommend it.

Franses and Ghijsels (1999) confirm the sensitivity of GARCH models to outliers in the data set. They examine four European stock indices using weekly data over the period 1983 to 1994. They find that correcting the data for outliers, where the most correction is needed for the weeks around

October 19, 1987, leads to improved forecasts of stock market volatility. McMillan, Speight and Gwilym (2000) also find that the forecasting ability of the GARCH model improves when the stock market crash of 1987 is excluded from the estimation sample.

From the empirical evidence, it emerges that a higher sampling frequency will increase the proportion of the variance of the squared return innovations that is attributable to the volatility process. It has also been shown that the forecasting performance of the GARCH class of models is sensitive to extreme within sample observations. As the data set starts after the stock market crash of 1987, this finding should not significantly affect the forecasting performance of most of the models under examination.

4.3 Data and Forecasting Procedure

The source of the data is DATASTREAM. The data set contains the daily values of the FTSE 100 index and the stock prices of thirty-nine FTSE 100 companies. The data covers the period January 4, 1988 to February 22, 1999, giving a total of 2,906 observation points. Further, for the period January 11, 1988 to February 22, 1999, the data is re-sampled at a four-weekly frequency, giving a total of 145 observation points. This allows the examination of whether the optimal forecasting model changes for the longer time interval. A recursive forecast method is used, the procedure extends the in-sample period as the forecast out-of-sample period is moved forward in time. It makes full use of the data and is particularly suited to variables that are relatively stable over the extended in-sample forecast period. To examine the stability of the forecast model, a rolling estimate of the optimal model for each company is performed. The original model is re-estimated for the period 5/1/1988 to 8/9/1998 and the volatility persistence level is calculated. The sample is then moved forward one working day, the model is estimated again and the volatility persistence is calculated. This procedure is repeated until one hundred and twenty values of the volatility persistence are calculated. If the optimal model is stable, the measure of volatility persistence should be stable. Likewise, if the volatility persistence is unstable, the optimal model will change over time.

For the recursive forecast method, the data is initially partitioned into the in-sample estimation period up to September 7, 1998 (as estimated in chapter three) and a one-step ahead forecast for the next observation is performed (September 8, 1998 for the daily data and October 5, 1998 for the four-weekly data). The observation for the initial forecasting period is then incorporated into the in-sample period. For the daily data, the initial model is then re-estimated for the period January 4, 1988 to September 8, 1998 and a one-step ahead forecast is calculated for September 9, 1998. In the case of the four-weekly data, the initial model is re-estimated for the period January 11, 1988 to October 5, 1998 and a one-step ahead forecast is calculated for November 2, 1998. This procedure of extending the in-sample period by one observation and then performing a one-step ahead forecast is repeated until one hundred and twenty daily and six four-weekly one-step ahead forecasts are generated. For evaluation purposes, the daily forecasts are put into six sets of twenty one-step ahead forecasts. The forecast periods are 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. The four-weekly forecasts are evaluated in one group. The one month forecasting horizon is used as it is within the time frame that most market participants are interested in.

4.4 Volatility Forecasting Models

Only details specific to volatility forecasting are dealt with in the section that follows below. For a full exposition of the GARCH type forecasting models see chapter two section two.

4.4.1 The GARCH Model

Out-of-sample forecasts of volatility are generated by the following GARCH(p, q) model:

$$h_{t+1} = \omega_T + \sum_{i=1}^{q} \alpha_{i,T} \epsilon^2_{t-i+1} + \sum_{i=1}^{p} \beta_{i,T} h_{t-i+1} \; ; \quad t = T, T+1, \ldots, T+\tau-1 \tag{4.4.1}$$

where τ denotes the number of out-of-sample observations, and the subscript T on a coefficient indicates that it is estimated conditional on the in-sample information set. For example, the GARCH(1, 1) model gives one-step ahead forecasts of volatility that are a weighted average of the long-run variance, the current volatility and the previously forecast variance for the current period. Volatility forecasts are increased following a large positive or negative return. This feature, in common with all the GARCH class models, can lead to inaccurate forecasts following an extreme in-sample return.

4.4.3 GJR Model

The GJR volatility forecast is expressed as:

$$h_{t+1} = \omega_T + \sum_{i=1}^{q} \alpha_{i,T} \epsilon^2_{t-i+1} + \sum_{i=1}^{p} \beta_{i,T} h_{t-i+1} + \gamma_t \epsilon^2_t D_t \tag{4.4.2}$$

for $t = T, T+1, \ldots, T+\tau-1$.

4.4.3 CGARCH Model

The CGARCH volatility forecast is generated by using:

$$h_{t+1} = q_{t+1} + \alpha(\epsilon_t^2 - q_t) + \beta(h_t - q_t) \tag{4.4.3}$$

$$q_{t+1} = \omega + \rho q_t + \phi(\epsilon_t^2 - h_t) \tag{4.4.4}$$

for $t = T, T + 1, \ldots, T + \tau - 1$.

4.4.5 ACGARCH Model

The ACGARCH volatility forecast is expressed as:

$$h_{t+1} = q_{t+1} + \alpha(\epsilon_t^2 - q_t) + \delta_s(D_t\epsilon_t^2 - 0.5q_t) + \beta(h_t - q_t) \tag{4.4.5}$$

$$q_{t+1} = \omega + \rho q_t + \phi(\epsilon_t^2 - h_t) + \delta_l(D_t\epsilon_t^2 - 0.5h_t) \tag{4.4.6}$$

for $t = T, T + 1, \ldots, T + \tau - 1$.

4.4.6 Historical Mean Model

The volatility forecast is generated by simply extrapolating the historical mean, that is, the unweighted average of volatility observed in-sample. Let s_t^2 denote the true volatility, thus the historical mean volatility forecast is expressed as:

$$h_{t+1} = \bar{s}_t^2 = \frac{1}{t}\sum_{j=1}^{t} s_j^2 \tag{4.4.7}$$

for $t = T, T + 1, \ldots, T + \tau - 1$..

4.4.7 Random Walk Model

The random walk model assumes that volatility fluctuates randomly, therefore, the optimal one step ahead volatility forecast is the current actual volatility:

$$h_{t+1} = s_t^2 \tag{4.4.8}$$

for $t = T, T+1, \ldots, T+\tau-1$.

4.4.8 Exponential Smoothing Model

The one-step ahead forecast of volatility is expressed as:

$$h_{t+1} = \phi_T h_t + (1 - \phi_T) s_t^2 \tag{4.4.9}$$

for $t = T, T+1, \ldots, T+\tau-1$. The forecast is a weighted function of the immediately preceding volatility forecast and current actual volatility. The coefficient ϕ is the smoothing parameter, $0 \leq \phi \leq 1$. For $\phi = 0$ the exponential smoothing model collapses to the random walk model, while as ϕ tends to one increased weight is given to the previous period volatility forecast.

4.4.9 Alternative Volatility Forecasting Model: Implied Volatility Forecast Model

The following sub-section only highlights the basic concept of implied volatility forecasting together with any benefits and disadvantages of using this forecasting procedure. For an extensive review of the literature on implied volatility estimates see Poon and Granger (2001).

A European call option is a financial instrument that gives the right to buy a stock at a given price (the strike price) on a set date in the future. According to Black and Scholes (1973) the price of an option depends on the current stock price, the risk free interest rate, the option time to maturity and the volatility of the return on the underlying asset. Once an option is traded, all the parameters except the volatility of the underlying asset are observable. Therefore, given the option price, an option pricing formula can be used to determine the market derived implied volatility estimate.

It could be expected that the implied volatility estimate would perform better than the GARCH type models at forecasting volatility. This is because the implied volatility estimate is forward looking as opposed to solely relying on historical stock prices. Nevertheless, implied volatility estimates suffer from many market driven pricing irregularities which can erode any advantages of using this method to forecast volatility. Frictions in the market, such as bid-ask spread, non synchronous trading and non-continuous trading etc. result in the implied volatility being significantly different from the true volatility. The Black-Scholes option pricing formula omits the clientele effect, that is, the segmented demand for certain types of option. For example, out of the money options can be compared to a lottery ticket whereby investors are happy to pay a price higher than the fair price because of the potential payoff.

4.5 Forecast Evaluation

Forecast errors occur when the actual value of a variable differs from the forecasted value. If a model is correctly specified, there are two sources of forecast error: coefficient uncertainty and residual uncertainty. Coefficient uncertainty arises because the estimated coefficients of an equation differ from the actual coefficients in a random fashion. Residual uncertainty occurs because the innovations, ϵ_t's, in the equation are unknown for the period being forecast, and are replaced by their expectations. Overall, the residuals have an expected value of zero, but individual errors can take non-zero values. Therefore, the greater the variation in the individual errors, the larger is the overall error in the forecasts.

In order to assess the accuracy of the volatility forecast estimators, a "true" measure of volatility is provided by the mean adjusted squared returns calculated over the in-sample and out-of-sample data. For the four-weekly volatility forecasts, the "true" measure of volatility is defined as the sum of the twenty mean adjusted squared daily returns. The historical mean, random walk and exponential smoothing models provide a benchmark for the comparative evaluation of the volatility forecasting performance of the GARCH type models. For the GARCH type models to be of any use for volatility forecasting, they would be required to outperform these three basic models. Forecasting ability is evaluated by using the root mean square error (RMSE), mean absolute error (MAE), median absolute percentage error (MedAPE) and the median squared error (MedSE), defined as follows:

$$RMSE = \sqrt{\frac{1}{\tau}\sum_{t=T+1}^{T+\tau}(h_t - s_t^2)^2} \qquad (4.5.1)$$

$$MAE = \frac{1}{\tau}\sum_{t=T+1}^{T+\tau}|h_t - s_t^2| \qquad (4.5.2)$$

$$MedAPE = median\left(\left|\frac{h_t - s_t^2}{s_t^2}\right|\right) \qquad (4.5.3)$$

$$MedSE = median((h_t - s_t^2)^2) \qquad (4.5.4)$$

where T denotes the number of in-sample observations and τ is the number of forecast data points. The RMSE, MAE and MedSE statistics are dependent on the scale of the variable being forecast. The MedSE, unlike the MAE and RMSE minimises the impact of outlying observations on the forecast evaluation. Compared with the MAE, the RMSE criterion weights greater forecast errors more heavily in the average forecast error penalty. The MedAPE statistic is a unit free measure of forecast errors, it expresses the forecast error as a percentage of the actual value. The MedAPE is used instead of the MAPE because it is less susceptible to the impact of outlying observations. The MAPE is asymmetric, that is, it puts a higher penalty on forecasts that exceed the actual value than on those that are less than the actual value. The MAPE has a lower bound of an error of one hundred percent, but the upper bound is limitless. The MedAPE reduces this bias in favour of lower forecasts.

Armstrong and Collopy (1992) use data on ninety annual and one hundred and one quarterly economic time series to examine the performance of the RMSE, MAPE MedAPE, percentage of forecasts better than the random walk (Percent better), geometric mean of the relative absolute error (GMRAE) and the Median relative absolute error (MedRAE) forecast measures. They recommend the use of the MedAPE for comparing forecast methods when many time series are examined. The widely used RMSE measure of forecast accuracy is found to have a low level of reliability. They state that the MAPE should not be used if large forecast errors are expected as it is biased in favour of low forecasts. They also found that the choice of error measure can affect the conclusions about the relative accuracy of forecasting methods. Nevertheless, the forecast error measures are found to converge when the number of series being examined is increased.

4.6 Daily Forecast Results

The rolling estimates of volatility persistence for the optimal model, over the one hundred and twenty periods, reveal that the volatility persistence for thirty companies and the index are stable. This shows that for these companies, the recursive method of forecasting should give better results. Figures 4.1 to 4.9 show the volatility persistence graphs for the nine companies that show some measure of instability. BAT industries, Bass, RMC and Royal & Sun Alliance Insurance have explosive measures of volatility persistence. Marks & Spencer and Reckitt & Colman have step shifts in the level of the volatility persistence, suggesting a one-off change in the optimal model. Standard Chartered appears to switch between two underlying models of the volatility process. Cadbury Schweppes and Pearson have incidents where the volatility persistence temporarily drops to a lower level. The inherent instability of the volatility persistence for these nine companies suggests that the optimal models are also unstable [2].

4.6.1 Forecast Appraisal by Forecast sub-periods for the GARCH type Models only

Tables 4.1 and 4.2 report the forecast error statistics for the recursive forecasts of the thirty-nine FTSE 100 companies and the index itself for the GARCH/GJR and CGARCH/ACGARCH, models [3]. Table 4.6 reports the best forecast model for the GARCH type models. Thirty-four companies can be represented by the two models. The six forecast periods are 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998,

[2] A rolling forecast procedure was also performed, it uses a fixed window for the in-sample period as the out of sample period moves forward. It can improve on the recursive forecast method when the forecast variable is more volatile. Overall, there was no appreciable difference between the results of the two different forecasting procedures. Therefore, only the recursive forecast results are analysed. The rolling forecast results can be seen in Tables 4.15 and 4.16 in Appendix 3.

[3] The Theil inequality coefficient (TIC) was also used in the initial forecast evaluation. The TIC statistic favours the GARCH/GJR model over the CGARCH/ACGARCH model. However, the TIC statistic was responsible for the majority of cases where one forecast evaluation criterion was inconsistent with the others. Consequently, the TIC statistic is not used in any further forecast evaluation and the results obtained from its use are not reported.

29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. Overall, as measured by the number of volatility spikes, the level of volatility is high in the first and second forecast periods. Seventeen companies in the first period have at least one daily return which exceeds 8 percent. The corresponding figure for the second forecast period is eleven companies. Against this, volatility is low in the fourth and sixth forecast periods, with only two and five companies respectively having daily returns that exceed 8 percent.

4.6.1.1 Sub-period one

Of particular note for the first forecast period, is the very poor forecasting performance of the GARCH model for BAT Industries and the GJR and CGARCH models for EMI. This is primarily due to the exceptional returns of 32.26 percent on 8/9/1998 for BAT Industries and -16.73 percent on 21/9/1998 for EMI. The high returns significantly raise the forecast of volatility for a number of days afterwards, thereby leading to a deterioration in forecasting performance. This highlights how the forecasting ability of the GARCH and GJR models are susceptible to extreme events. For the initial forecasting period, the forecasts for Bass, Blue Circle, CGU, Diageo, Enterprise Oil, General Electric, Ladbroke, Legal & General, Prudential, RMC, Rank Group, Reuters, Royal & Sun Alliance Insurance, Royal Bank of Scotland and Standard Chartered are also similarly affected, although to a lesser extent.

It is also the case that the ranking of the forecast models is highly dependent on the choice of error statistic. The RMSE statistic favours the GARCH/GJR model for nineteen companies as opposed to eighteen, nineteen and fourteen companies respectively for the MAE, MedAPE and MedSE forecast evaluation criteria. The MedSE statistic favours the CGARCH/ACGARCH model while the MAE and MedAPE statistics slightly prefer the GARCH/GJR model. The difference arises because the first period is characterised by high levels of volatility together with a high impact of volatility spikes. The RMSE statistic weights greater forecast errors more heavily in the average forecast error penalty. Therefore, the degree of losses associated with higher forecast errors is the critical factor when choosing between the models. A risk averse investor should choose the GARCH/GJR model over the CGARCH/ACGARCH model. An investor with a lower degree of risk aversion should use the CGARCH/ACGARCH model.

4.6.1.2 Sub-period two

For the second forecast period, as in the first forecast period, a number of companies have forecasts that are affected by particularly large returns. The eleven companies are CGU, Diageo, ICI, Legal & General, Natwest Bank, Prudential, Reuters, Royal & Sun Alliance Insurance, Scottish & Newcastle, Standard Chartered and Unilever. Seven of these companies also had at least one large return in the first forecast period. Once again, the ranking of the forecasts is highly dependent on the choice of forecast evaluation criterion. The RMSE statistic favours the GARCH/GJR model. The MAE, MedAPE and MedSE statistics favour the CGARCH/ACGARCH model. Overall, a similar conclusion to the first forecast period can be made, a risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the CGARCH/ACGARCH model.

4.6.1.3 Sub-period three

In the third forecast period, the forecast performance for a number of companies is affected by some large returns, especially so for EMI and Reckitt & Colman that have absolute returns exceeding 15 percent for a single day. In contrast to the first two forecasting periods, the forecast results show more agreement among the four forecast error statistics on the best forecasting model. Nineteen companies have the four forecast error statistics in agreement on the best forecasting model. Of these companies, eight favour the GARCH/GJR model, with the CGARCH/ACGARCH model being preferred for eleven companies. The RMSE and MAE criteria favour the GARCH/GJR model for nineteen and twenty companies respectively. The CGARCH/ACGARCH model is preferred for nineteen and twenty companies respectively for the MedAPE and MedSE statistics. As in the first two forecast periods, a risk averse investor should choose the GARCH/GJR model while an investor with a lower degree of risk aversion should choose the CGARCH/ACGARCH model.

4.6.1.4 Sub-period four

The fourth forecast period has a lower level of volatility with only Associated British Foods and General Electric having forecasts that are affected by large returns. Broadly speaking, there is a strong agreement between the different forecast error statistics. Eighteen companies have the four forecast error statistics in agreement on the best forecasting model. The GARCH/GJR and CGARCH/ACGARCH models are each preferred for nine of the companies respectively. The RMSE statistic slightly favours the CGARCH/ACGARCH model while the MAE and MedSE criteria favour the GARCH/GJR model, the MedAPE statistic has no overall preference. Therefore, an investor should choose the GARCH/GJR model no matter what their degree of risk aversion.

4.6.1.5 Sub-period five

In the fifth forecast period, eight companies have forecasts that are affected by at least one instance of an unusually large return. Exceptionally large returns of 14.43 percent for BAT Industries, -14.69 percent for Marks & Spencer and 12.77 percent for Standard Chartered result in a poorer forecast performance. Overall, while volatility is lower than in the first two forecast periods, volatility spikes have a notable impact. There is less agreement between the forecast error statistics than in the previous forecast period. All the forecast error statistics are in agreement on the best forecast model for only ten companies. The RMSE and MedSE criteria favour the CGARCH/ACGARCH model while the MAE and MedAPE statistics favour the GARCH/GJR model. In contrast to the earlier forecast periods, a risk averse investor should choose the CGARCH/ACGARCH model while a more risk neutral investor should choose the GARCH/GJR model.

4.6.1.6 Sub-period six

The sixth forecast period has less forecast volatility with only BT, Ladbroke, Rank Group, Reckitt & Colman and Sainsbury exhibiting large volatility spikes. Ladbroke has an especially large return of 15.23 percent on 8/2/1999 resulting in an RMSE value of fifty-one. All the forecast evaluation criteria prefer the CGARCH/ACGARCH model. Therefore, all investors should choose the CGARCH/ACGARCH model.

4.6.1.7 Summary

For the six forecast periods as a whole, no single model is clearly superior for any given type of investor. Nevertheless, a pattern does emerge when the level of volatility is taken into account. At high levels of volatility, as in the first two forecast periods, a risk averse investor should choose the GARCH/GJR model while an investor with a lower degree of risk aversion should choose the CGARCH/ACGARCH model. At an intermediate level of volatility, as in the fifth and sixth forecast periods, the preferences begin to reverse ie. a risk averse investor should choose the CGARCH/ACGARCH model while a more risk neutral investor should choose the GARCH/GJR model in the fifth forecast period and the CGARCH/ACGARCH in the sixth forecast period. At a low level of volatility, as seen in the fourth forecast period, the GARCH/GJR model is the optimal choice for all investors. Therefore, from the point of view of a risk averse investor, the GARCH/GJR model is the best at higher and lower volatility levels than normal while the CGARCH/ACGARCH model is optimal at intermediate volatility levels.

4.6.2 Forecast Appraisal by Forecast sub-periods including Benchmark Models

Tables 4.1 to 4.5 report the forecast evaluation criteria for the recursive forecasts of the thirty-nine FTSE 100 companies and the index itself for the GARCH/GJR, CGARCH/ACGARCH, Historical Mean, Random Walk and Exponential Smoothing models. Table 4.7 reports the best forecast model for each forecast evaluation criterion in each of the six forecast periods.

4.6.2.1 Sub-periods one, two and three

The first three periods are characterised by high volatility levels with the first two periods having the highest volatility. For the RMSE criterion, the exponential smoothing model is ranked ahead of the GARCH/GJR and CGARCH/ACGARCH models. A risk averse investor should choose the exponential smoothing model ahead of the GARCH type models. The historical mean model strongly outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. Clearly, a more risk neutral investor should choose the historical mean model.

4.6.2.2 Sub-period four

The GARCH/GJR and CGARCH/ACGARCH models give a better forecasting performance in a period that is characterised by low volatility levels. For the RMSE statistic, the CGARCH/ACGARCH ranks jointly as the best model together with the historical mean model. The next best models are the exponential smoothing and GARCH/GJR models. Once again, the MAE, MedAPE and MedSE statistics strongly favour the historical mean model with thirty seven, twenty-one and twenty-eight cases respectively. For the median forecast evaluation criteria, the random walk model ranks second, which is to be expected in a period of low volatility. Overall, the historical mean model is the optimal choice regardless of the risk preferences of the investor.

4.6.2.3 Sub-period five

The fifth forecast period has an intermediate level of volatility. The RMSE criterion strongly favours the exponential smoothing model, the CGARCH/ACGARCH and GARCH/GJR models rank second and third respectively. As in the earlier forecast periods, the historical mean model strongly outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. The MedAPE criterion, which gives the lowest penalty to greater forecast errors, ranks the random walk model as second best with twelve companies favouring this forecasting model. The MedSE statistic only favours the random walk model for three companies. This is to be expected, as at intermediate and higher volatility levels, a no change forecast will perform poorly for criteria with higher forecast error penalties. Overall, a risk averse investor should choose the historical mean model and a more risk neutral investor should choose the random walk model.

4.6.2.4 Sub-period six

The sixth forecast period has low volatility levels and the models give a similar forecasting performance to the preceding period. The exponential smoothing model is the best model for the RMSE criterion followed by the CGARCH/ACGARCH model. The historical mean model strongly outperforms the other models for the MAE, MedAPE and MedSE forecast error criteria. Therefore, a risk averse investor should choose the exponential smoothing model and a more risk neutral investor should choose the historical mean model.

4.6.2.5 Summary

For the six forecast periods as a whole, the historical mean model outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. In contrast, except for forecast period four that has a low level of volatility, the exponential smoothing model is the best choice of forecasting model for the RMSE forecast evaluation criterion. Taking the five higher volatility forecast periods together, the CGARCH/ACGARCH and GARCH/GJR models rank as the second and third best volatility forecast models. In the fourth forecast period, the historical mean model ranks as joint best with the CGARCH/ACGARCH for the RMSE statistic. These results can be explained by the different penalties the forecast evaluation criteria give to higher forecast errors. The RMSE criterion weights greater forecast errors more heavily in the average forecast error penalty. Therefore, a forecast based on historical mean volatility would only perform well in periods when volatility is low. Likewise, a no change forecast of volatility is likely to perform poorly when judged by a high penalty forecast evaluation criterion. The MAE, MedAPE and MedSE criteria have much lower penalties for greater forecast errors. The historical mean model is then likely to perform particularly well, as on average the historical volatility level will be near the actual volatility. The exponential smoothing model has features in common with the GARCH type models. For example, both the GARCH(1, 1) and exponential smoothing models have a one-step ahead forecast that features the immediately preceding volatility forecast and current actual volatility. Except for the lowest volatility period, the exponential smoothing model is a better volatility forecaster than the GARCH type models when judged by the RMSE criterion. Overall, the GARCH type models are outperformed by the benchmark models, therefore, it is not possible to recommend use of the GARCH type models for forecasting daily volatility.

4.7 Four-Weekly Forecast Results

Tables 4.8 to 4.12 report the forecast evaluation criteria for the recursive forecasts of the thirty nine FTSE 100 companies and the index itself for the GARCH/GJR, CGARCH/ACGARCH, Historical Mean, Random Walk and Exponential Smoothing models. Table 4.13 reports the best forecast model for the GARCH type models and Table 4.14 reports the best overall forecast model.

Considering the GARCH type models on their own, the RMSE, MAE and MedAPE statistics prefer the GARCH/GJR model while the MedSE statistic favours the CGARCH/ACGARCH model. Out of the twenty-five cases where a comparison between the GARCH type models is possible, there are fifteen cases where all four forecast evaluation criteria are in agreement. The GARCH/GJR model is preferred for nine cases as compared to six cases for the CGARCH/ACGARCH model. Therefore, an investor should choose the GARCH/GJR over the CGARCH/ACGARCH model. In contrast to the daily forecasts, the four-weekly forecasts are much more favourable to the GARCH type models when compared against the benchmark models. The GARCH/GJR model ranks as the best model for the RMSE criterion and second best for the MAE, MedAPE and MedSE forecast evaluation criteria. A risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the exponential smoothing model.

4.8 Conclusions

Considering the GARCH type models on their own, a pattern does emerge for the daily volatility forecasts. At high levels of volatility, a risk averse investor should choose the GARCH/GJR model while an investor with a lower degree of risk aversion should choose the CGARCH/ACGARCH model. At an intermediate level of volatility, the preferences begin to reverse, that is, a risk averse investor should choose the CGARCH/ACGARCH model while a more risk neutral investor should choose the GARCH/GJR model. At a low level of volatility, the GARCH/GJR model is the optimal choice for all investors. Therefore, from the point of view of a risk averse investor, the GARCH/GJR model is the best at higher and lower volatility levels than normal while the CGARCH/ACGARCH model is optimal at intermediate volatility levels. A more risk neutral investor should choose the CGARCH/ACGARCH model in intermediate to high volatility situations and the GARCH/GJR model at low levels of volatility. For the four weekly forecasts, an investor should choose the GARCH/GJR model over the CGARCH/ACGARCH model regardless of the level of volatility.

Including the benchmark models, the historical mean model strongly outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. The exponential smoothing model is the best choice of forecasting model for the RMSE criteria except when volatility is low. The CGARCH/ACGARCH and GARCH/GJR models perform relatively better when judged by the RMSE criterion, they rank as the second and third best volatility forecast models. When volatility is low, the historical mean model ranks as joint best with the CGARCH/ACGARCH for the RMSE statistic. These results can be explained by the different penalties the forecast evaluation criteria give to higher forecast errors. The RMSE criterion weights greater forecast errors more heavily in the average forecast error penalty. Therefore, a forecast based on historical mean volatility would only perform well in periods when volatility is low. The MAE, MedAPE and MedSE criteria have much lower penalties for greater forecast errors. The historical mean model is then likely to perform particularly well, as on average the historical volatility level will be near the actual volatility. The exponential smoothing model has features in common with the GARCH type models in that one-step ahead forecasts feature the immediately preceding volatility forecast and current actual volatility. Except for the lowest volatility period, the exponential smoothing model is a better volatility forecaster than the GARCH type models when judged by the RMSE criterion. Overall, the GARCH type models are outperformed by the benchmark models for the daily forecasts, therefore, it is not possible to recommend use of the GARCH type models for forecasting daily volatility. In contrast to the daily forecasts, the four-weekly forecast are much more favourable to the GARCH type models when compared against the benchmark models. The GARCH/GJR model ranks as the best model for the RMSE criterion and second best for the MAE, MedAPE and MedSE forecast evaluation criteria. A risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the exponential smoothing model.

Chapter 5 - Volatility-Volume Interaction

5.1 Introduction

It has long been recognised that the variance of stock price changes may be related to trading volume. Clark (1973) suggests a mixture of distributions model where stock returns and trading volumes are jointly dependent on the same underlying, latent information flow variable. Stock price changes would then follow a mixture of distributions in which the speed of information flow is the mixing variable. Thus, if the information arrivals are serially dependent, the squared errors will be correlated. The ARCH class of models is able to capture this correlation. It has been recognised that the mixture of distributions hypothesis (MDH) rationalisation for GARCH effects is open to doubt, as can be seen in the following literature review. Therefore, in the current chapter, I will test whether the MDH is valid. If the hypothesis is correct, introducing volume into the GARCH type equations should lead to the GARCH effects vanishing. If the GARCH effects are still present, the MDH will have been shown to be flawed. The volatility volume analysis is also extended to CGARCH/ACGARCH models, this adds to the literature on volatility volume models because work using this model has not been undertaken before. This has an analogy with the modified MDH model of Andersen (1994, 1996) whereby the effects of information flows on temporary volatility can be examined.

The remainder of the chapter is organised as follows. Section two details the empirical evidence relating to volatility-volume models with section three detailing the volatility-volume models used in testing the MDH. Section four contains information about the data set and test methods used. Section five describes the results from the volatility-volume models while section six offers some concluding remarks.

5.2 Empirical Evidence

Lamoureux and Lastrapes (1990) find that volatility persistence in individual stock returns can be explained by current trading volume as suggested by Clark's (1973) model. They achieved this by examining whether ARCH effects disappear when trading volume is used as a proxy for the rate of information arrival. When trading volume is included in the conditional variance specification, its coefficient is highly significant for all the stocks considered. In addition the ARCH effects become negligible for most of the stocks. They conclude that ARCH is a manifestation of the daily time dependence in the rate of information arrival to the market for individual stocks.

Lamoureux and Lastrapes (1994) test a mixture model for volume of trade and returns. The two variables are generated by independent, identically distributed shocks and a single common factor, the speed of information arrival to the market. In contrast to the results found in their 1990 study, they find that serial correlation in squared price changes is independent of the volume of trade.

The findings of other authors have brought the conclusion of Lamoureux and Lastrapes (1990) into doubt. Hiemstra and Jones (1994) examine whether the non-linear causality from volume to returns is due to volume acting as a proxy for the information flow in the stochastic process generating the stock return variance as Clark (1973) proposes. They find that after controlling for volatility persistence in returns, there is still evidence of non-linear causality from volume to returns. Therefore, ARCH cannot be due to serial correlation in trading volumes alone.

Omran and McKenzie (2000) also find results different from those of Lamoureux and Lastrapes (1990). They use data from fifty-seven FTSE 100 companies over the period January 4, 1988 to February 28, 1994. The main section of the results contains the fifty companies whose volume data display significant autocorrelations. Their initial investigations give results consistent with those of Lamoureux and Lastrapes, that is, volatility persistence becomes negligible when trading volume is introduced into the variance equation of price changes. They also examine the square of the standardised residuals for serial correlation. They find that although volatility persistence is negligible, ARCH effects are still present in the residuals of the model. They suggest that this could be due to the fact that serial dependence in the volume of trade and past conditional volatilities have a similar information content. This is because past conditional volatilities are functions of previous volumes of trade. Also, the volume of trade is highly serially correlated. As a consequence, either of them can be used in the conditional variance specification but both are not needed. As mentioned earlier, the volume of trade does not capture all of the linear dependence in the conditional volatility. Therefore, some GARCH modelling is still necessary.

Sharma, Mougoue and Kamath (1996) use data on the New York Stock Exchange index for the period January 2, 1986 to December 29 1989. They find that the introduction of volume as a explanatory variable in the conditional variance equation dampens but does not eliminate the GARCH effects. They find that while volume contributes significantly in explaining GARCH effects, there may be other variables beside volume that contribute to the heteroscedasticity in market returns.

Andersen (1996) uses data on five US common stocks for the period January 2, 1973 to December 23, 1991 to test the modified MDH model as put forward in Andersen (1994). The model modifies the standard MDH to take account of asymmetric information and noise traders. It has informed investors who obtain private information that they can use to their advantage. Thus, there is a price discovery phase whereby the sequence of trades reveals the pricing implications of the private information. The information flows affect temporary volatility. The use of CGARCH/ACGARCH models to examine how information flows affect temporary volatility has an analogy to this. Andersen shows that specification tests support the modified MDH representation and that it vastly outperforms the standard MDH.

5.3 Models

The discussion below relates to the volume part of the volatility-volume GARCH type models. A fuller exposition of the details of the underlying models is given in chapter two, section two.

5.3.1 GARCH/GJR Volatility-Volume Models

The conditional mean model as with all the following GARCH type models is an AR(1) model.

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{5.3.1}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} + \delta_v V_t \tag{5.3.2}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero. V_t is the volume of trade in millions of shares. The above volatility-volume model is subject to an unquantified bias due to the fact that volume and price changes are contemporaneously correlated. The problem arises because past conditional volatilities are functions of previous volumes of trade. Further, the volume of trade variable is highly serially correlated and this can result in a high correlation between the explanatory variables used. To circumvent this problem while still testing the validity of the MDH, lagged volume and unexpected volume are used. Unexpected volume is arrived at by fitting an ARMA (autoregressive moving average) model to the volume of trade, and the uncorrelated innovations are used as an explanatory variable in the volatility-volume model instead of volume of trade itself.

The volatility-volume GARCH/GJR model with lagged volume is given by:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{5.3.1}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} + \delta_v V_{t-1} \tag{5.3.3}$$

where V_{t-1} is the volume of trade in millions of shares for period t - 1. The volatility-volume model with unexpected volume is given by:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{5.3.1}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} + \delta_v V_t^* \tag{5.3.4}$$

where V_t^* is the innovation in the volume of trade, that is, the residuals of a fitted ARMA model for volume of trade.

5.3.2 CGARCH/ACGARCH Volatility-Volume Models

The CGARCH/ACGARCH volume model modifies the underlying model by including a volume term in the transitory component [4]. The CGARCH/ACGARCH volume model is given by:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{5.3.1}$$

$$h_t = q_t + \alpha(\epsilon^2_{t-1} - q_{t-1}) + \delta_s(D_{t-1}\epsilon^2_{t-1} - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \delta_{vs}V_t \tag{5.3.5}$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon^2_{t-1} - h_{t-1}) \tag{5.3.6}$$

The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero. The CGARCH/ACGARCH lagged volume and unexpected volume models adapt equation (5.3.5) to give:

$$h_t = q_t + \alpha(\epsilon^2_{t-1} - q_{t-1}) + \delta_s(D_{t-1}\epsilon^2_{t-1} - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \delta_{vs}V_{t-1} \tag{5.3.7}$$

$$h_t = q_t + \alpha(\epsilon^2_{t-1} - q_{t-1}) + \delta_s(D_{t-1}\epsilon^2_{t-1} - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \delta_{vs}V^*_t \tag{5.3.8}$$

5.4 Data and Test Methods

The data set for the stock returns is the same as described in Chapter three, section one with the

[4] A CGARCH/ACGARCH model specification with the contemporaneous volume term in the permanent component was also estimated. The volume term in the permanent component was significant for seventeen companies. However, the reduction in permanent component volatility persistence was minimal with only one company having a substantial reduction in permanent component volatility persistence. Nevertheless, the permanent component volatility persistence for this company did remain significant. Consequently, the investigation of volume terms in the permanent component was stopped and the results are not reported.

addition of data on the daily volume of trade for each stock. The source of the data is DATASTREAM. For the test methods used in estimating GARCH type volatility-volume models, see chapter three section three.

5.5 Volatility-Volume Model Results

5.5.1 GARCH/GJR Volume Model Results

The AR(1)-GARCH/GJR(p, q) volume model estimates for the thirty-nine FTSE 100 companies are reported in Table 5.1. The coefficient of volume is significant at the five percent level for all the companies. The level of the volatility persistence is dramatically reduced as compared with the results for the AR(1)-GARCH/GJR(p, q) model reported in Table 3.2. The coefficient on the lagged conditional variance term is non-significant for seven of the companies while the coefficients on the lagged squared residual term remain significant for all the companies. Overall, the introduction of volume as an explanatory variable in the conditional variance has dampened but not eliminated the GARCH effects. The residual diagnostics for the model reported in Table 5.2 reinforce this finding. The Ljung-Box statistics show serial dependence in the squares of the standardised residuals for all of the companies. At the five percent significance level, the Q_5 and Q_{10} statistics are significant for all the companies. Likewise, the ARCH-LM test results confirm the findings of the Ljung-Box test of serial correlation. Due to the problems of contemporaneous correlation of the above model, the lagged and unexpected volume model results need to be examined before formulating any possible conclusions.

The AR(1)-GARCH/GJR(p, q) lagged and unexpected volume model estimates for the thirty-nine FTSE 100 companies are reported in Tables 5.3 and 5.5. The lagged volume results show that the lagged volume term is only significant for eight companies. This can indicate that lagged volume is a poor substitute for the contemporaneous volume in that is has little explanatory power in the variance equation. The results show only minimal reductions in volatility persistence as compared with the AR(1)-GARCH/GJR(p, q) results reported in Table 3.2. In contrast, the unexpected volume results show that the coefficient of unexpected volume is significant for all of the companies with the volatility persistence being notably reduced. Nevertheless, the coefficient on the lagged conditional variance term is significant for all of the companies while the coefficients on the lagged squared residual term are only non-significant for Land Securities. The residual diagnostics for the unexpected volume model reported in Table 5.6 show that a number of companies have a highly significant GARCH pattern in the squared standardised residuals. The Ljung-Box statistic at lag five is significant for seventeen companies while the ARCH-LM results confirm the findings of the Ljung-Box test.

Overall, the GARCH/GJR volume results show that serial dependence in the volume of trade only explains some but not all of the volatility persistence of the GARCH model. As the GARCH effects do not vanish with the introduction of volume of trade into the variance equation, the MDH is flawed, and provides justification for the use of alternative specifications.

The AR(1)-CGARCH/ACGARCH volume model estimates for the thirty-nine FTSE 100 companies are reported in Table 5.7. The coefficient of volume is significant at the five percent level for all the companies bar Pearson. As compared with the results for the AR(1) CGARCH/ACGARCH model reported in Table 3.5, the level of the volatility persistence of the transitory component is lower while there are only minimal reductions in the volatility persistence of the permanent component. The transitory component parameters are non-significant for six companies. Two of these companies, BT and ICI, do not have significant serial correlation in the squared standardised residuals. This supports the MDH hypothesis that ARCH effects are a manifestation of serial dependence in the rate of information arrival. Overall, with thirty-seven companies not supporting the MDH, this represents very weak evidence in favour of the hypothesis. Against this, the results are likely to be biased due to the problem of contemporaneous correlation.

The AR(1)-CGARCH/ACGARCH lagged volume model estimates for the thirty-nine FTSE 100 companies are reported in Table 5.9. The lagged volume results show that the lagged volume term is significant for nineteen companies. As compared with the results for the AR(1) CGARCH/ACGARCH model reported in Table 3.5, the level of the volatility persistence of the transitory component is lower while the volatility persistence of the permanent component is virtually unchanged. The transitory component parameters are non-significant for eight companies. These eight companies do not have significant serial correlation in the squared standardised residuals.

The AR(1)-CGARCH/ACGARCH unexpected volume model estimates for the thirty-nine FTSE 100 companies are reported in Table 5.11. The unexpected volume results show that the lagged volume term is significant for all of the companies. As compared with the results for the AR(1) CGARCH/ACGARCH model reported in Table 3.5, the level of the volatility persistence of the transitory component is generally lower while there are only minimal reductions in the volatility persistence of the permanent component. The transitory component parameters are non-significant for only CGU. The Ljung-Box and ARCH-LM statistics, as shown in Table 5.12, indicate that CGU has no serial correlation in the squared standardised residuals. Therefore, the unexpected volume results show virtually no support for the MDH with only one company providing any evidence in favour of the hypothesis.

The CGARCH/ACGARCH volume results show that serial dependence in the volume of trade only explains all of the transitory volatility persistence for a small number of the companies. The volume and unexpected volume CGARCH/ACGARCH models provide very little support for the MDH with only the lagged volume results providing any meaningful support. On balance, the CGARCH/ACGARCH results provide more evidence against the MDH.

5.6 Conclusions

Overall, the GARCH/GJR volume results show that serial dependence in the volume of trade only explains some but not all of the volatility persistence of the GARCH model. As the GARCH effects do not vanish with the introduction of volume of trade into the variance equation, this provides strong evidence against the MDH. The CGARCH/ACGARCH volume results provide little support for the MDH. Only the lagged volume CGARCH/ACGARCH results provide some consistent support for the MDH. Nevertheless, companies that support the MDH are out numbered four to one by companies providing evidence against the MDH. Overall, the evidence supports the idea that the MDH only explains some of the GARCH effects and that there may be other variables beside volume that contribute to the heteroscedasticity in market returns.

Chapter 6 - Stochastic Volatility Models

6.1 Introduction

A problem with GARCH type models is that the variance equation does not contain a separate innovation term. To avoid this problem, Taylor (1986) formulates the stochastic volatility model. The key feature of the model it that unlike ARCH and GARCH models, both the mean and log volatility have separate error terms. The conditional volatility does not depend on past observations, but on some unobserved components or latent structure. One interpretation of the latent volatility process is that it represents the random and uneven flow of information. As the MDH is found to be lacking in explanatory power, this provides motivation for considering models of the stochastic volatility class that are founded on extensions of the MDH as exemplified by Andersen (1994, 1996). In common with the GARCH model, the stochastic volatility model has an unconditional distribution for the error term that displays kurtosis. Nevertheless, the kurtosis level of the stochastic volatility model is more in line with the levels found in financial data. An improved model is given by Harvey and Shephard (1996) who formulate an asymmetric stochastic volatility model to capture any asymmetric response of volatility to past shocks.

The remainder of the chapter is organised as follows. Section two gives details about the structure of stochastic volatility models, while section three contains the empirical evidence relating to the modelling and forecasting ability of the models. Section four contains information about the data set. Section five describes the estimation procedure, section six gives the test methods used and section seven details the estimation results. Sections eight and nine describe the forecasting procedure and the methods used to evaluate their performance. Sections ten and eleven give the forecast results, while section twelve delivers some concluding remarks.

6.2 Models

6.2.1 Stochastic Volatility Model

Stochastic volatility models are an alternative to ARCH models, in that instead of the conditional variance being a function of past observations, they specify that it follows an unobserved component or latent stochastic process. Andersen (1994, 1996) shows that one interpretation of the latent stochastic process, h_t, is that it represents the random and uneven flow of information, which follows the work of Clark (1973). Unlike GARCH type models, both the mean and the log-volatility equations have separate error terms. The discrete time stochastic volatility model of Taylor (1986) is given by:

$$y_t = \Delta \log p_t - \mu = \exp(h_t/2) Z_t \tag{6.2.1}$$

$$h_{t+1} = \delta + \Phi h_t + \eta_t \tag{6.2.2}$$

where $Z_t \sim \text{IID}(0, 1)$, $\eta_t \sim \text{ID}(0, \sigma_\eta^2)$, y_t denotes the continuous return of an asset corrected for the unconditional mean, p_t denotes the price of an asset at time t, and δ and Φ are constants. It is assumed that the error terms are uncorrelated. The coefficient Φ represents the level of volatility persistence, with a half-life calculated as above. When Φ is less than one in absolute value, h_t, and therefore y_t, is stationary. If the process is stationary, h_t has the following unconditional moments:

$$E[h_t] = \frac{\delta}{(1 - \Phi)} \quad , \quad Var[h_t] = \frac{\sigma_\eta^2}{(1 - \Phi^2)} \tag{6.2.3}$$

The stochastic volatility model has fatter tails than the corresponding normal distribution provided that the variance of the volatility process is greater than zero. This kurtosis is consistent with the observed characteristics of many financial time series.

Harvey, Ruiz and Shephard (1994) put forward the linear state space formulation of the above model. It is given by taking the logarithm of the squared returns in equation (6.2.1):

$$\ln(y_t^2) = h_t + \ln(Z_t^2) = h_t + E_t[\ln(Z_t^2)] + \xi_t \tag{6.2.4}$$

$$h_{t+1} = \delta + \Phi h_t + \eta_t \tag{6.2.2}$$

where $\xi_t \equiv \ln(Z_t^2) - E_t[\ln(Z_t^2)]$, $\xi_t \sim ID(0, \sigma_\xi^2)$. The residual ξ_t is white noise, therefore, $\ln(y_t^2)$ is the sum of a constant, an AR(1) component and a white noise component. Equation (6.2.4) is the measurement equation in the state space system while equation (6.2.2) is the transition equation. The disturbance term $\ln(Z_t^2)$ has a mean and variance that depend on the distribution of Z_t. Abromowitz and Stegun (1970) show that if Z_t is standard normal, the mean is minus 1.279 and the variance is 4.934. By subtracting the unconditional expected value from (6.2.2), the state space model can be written as:

$$\ln(y_t^2) = \Lambda + h_t + \xi_t \tag{6.2.5}$$

$$h_{t+1} = \Phi h_t + \eta_t \tag{6.2.6}$$

where $\Lambda = \ln(k^2) + E_t[\ln(Z_t^2)]$ and $\ln(k^2) = (\frac{\delta}{1 - \Phi})$. The coefficient k models the effect of the constant term δ in the original log-variance equation. The Monday effect can be examined by modifying the measurement equation via the inclusion of a dummy variable term M_t, such that $M_t = 1$ when the day of the week is Monday and zero otherwise. The measurement equation becomes:

$$\ln(y_t^2) = \Lambda + \lambda_d M_t + h_t + \xi_t \tag{6.2.7}$$

6.2.2 Asymmetric Stochastic Volatility Model

Harvey and Shephard (1996) formulate a stochastic volatility model in which the error terms of the return and transition equations are allowed to be correlated. The asymmetry in the conditional variance allows the model to capture the 'leverage effect'. It is assumed that the joint distribution of Z_t and η_t is symmetric, that is, $f(Z_t, \eta_t) = f(-Z_t, \eta_t)$. This allows the disturbance terms in the state space form to be uncorrelated. The standard linear state space form contains no information on the correlation between Z_t and η_t, as this information is lost when the observations are squared. Conditioning on the signs of the observation y_t allows this information to be recovered. The sign of y_t is denoted by s_t where $s_t = 1$ if $Z_t > 0$ and $s_t = -1$ if $Z_t < 0$. The linear state space form with correlated errors is given by:

$$\ln(y_t^2) = \Lambda + h_t + \xi_t \tag{6.2.5}$$

$$h_{t+1} = \Phi h_t + s_t \mu^* + \eta_t^* \tag{6.2.8}$$

$$\begin{pmatrix} \xi_t \\ \eta_t^* \end{pmatrix} \mid s_t \sim ID\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\xi^2 & \gamma^* s_t \\ \gamma^* s_t & \sigma_\eta^2 - \mu^{*2} \end{pmatrix} \right) \tag{6.2.9}$$

where $\mu^* \equiv E[\eta_t | s_t = 1]$ and $\gamma^* \equiv cov(\eta_t, \xi_t | s_t = 1)$. Likewise $\mu^* \equiv -E[\eta_t | s_t = -1]$ and

$\gamma^* \equiv -cov(\eta_t, \xi_t | s_t = -1)$. It is necessary to make a distributional assumption about η_t and Z_t in order to evaluate the correlation between the errors, ρ. If Z_t and η_t are bivariate normal, then Harvey and Shephard (1996) show that the following must hold: $\mu^* = \rho\sigma_\eta\sqrt{2/\pi}$ and $\gamma^* = 1.1061\rho\sigma_\eta$. The 'leverage effect' is associated with a negative value of ρ. This is equivalent to μ^* and γ^* being less than zero.

6.3 Recent Empirical Evidence

The following literature review concentrates on articles comparing the performance of GARCH type and stochastic volatility models using the quasi maximum likelihood estimation method. For an extensive review of stochastic volatility models see Ghysels, Harvey and Renault (1996).

Harvey and Shephard (1996) look at CRSP daily returns on a value weighted U. S. Market index for July 3, 1962 to December 31, 1987 as previously used by Nelson (1991) to illustrate his EGARCH model. They find a negative correlation between the innovations, Z_t and η_t, which confirms the result of Nelson (1991). Overall, there is little residual dependence in the residuals, with the model having a similar level of performance to the EGARCH model.

Heynen and Kat (1994) evaluate the forecast performance of the random walk, GARCH(1, 1), EGARCH(1, 1) and stochastic volatility predictors. They use daily data for the period January 1980 to December 1992 on the S & P 500, Nikkei 225, FTSE 100, CAC General, Hang Seng and the Australian All Ordinary stock indices. They also examine data for five different currencies. Overall, they find that the stochastic volatility model is the best volatility predictor for the stock indices. For the currencies, the best volatility predictor is the GARCH(1, 1) model. They ascribe this to the fact that for equity markets the price volatility reaction to information flows cannot be described adequately by historical price information.

Hansson and Hördahl (1998) evaluate different GARCH type models and stochastic volatility models. They use the Swedish OMX index daily closing prices for the period January 2, 1984 to February 1, 1996. The index consists of the thirty most actively traded stocks on the Stockholm exchange. They find significant asymmetry in the conditional variance of the EGARCH and stochastic volatility models, giving strong evidence for the existence of a 'leverage effect'. It is found that the stochastic volatility models fit the data considerably better than the GARCH models. Within both types of models, asymmetric and seasonal (weekend effect) specifications are found to give improved ability to fit the data. Overall, the best in-sample model is the asymmetric restricted stochastic volatility model with a seasonal weekend component.

Hsieh (1991) also finds that stochastic volatility models perform better than GARCH type models. He examines the weekly CRSP value weighted and equally weighted portfolios for the period 1963 to 1987 together with S & P 500 weekly data for the period 1963 to 1987. Daily data for the S & P 500 for the years 1983 to 1989 is also evaluated. Hsieh finds that ARCH, GARCH and EGARCH filters do not remove all nonlinear dependencies in the series as measured by a number of residual diagnostics. In contrast, when an autoregressive stochastic volatility filter is applied to the data, no remaining nonlinear dependencies are detected.

Danielsson (1994) examines eight years of daily observations of the S & P 500 index for the years 1980 to 1987. The stochastic volatility model with serial correlation in the latent variable is compared to ARCH, GARCH, EGARCH and IGARCH models by examining the Schwarz criteria. Danielsson finds that the best stochastic volatility model has maximum likelihood values that are higher than those for the best of the ARCH models, EGARCH, while having fewer parameters.

6.4 Data

The data set contains the daily values of the FTSE 100 index and the stock prices of thirty-nine FTSE 100 companies. In keeping with the analysis of chapter four, the data covers the period January 4, 1988 to February 22, 1999, giving a total of 2,906 observation points. Further, for the period January 11, 1988 to February 22, 1999, the data is re-sampled at a four-weekly frequency, giving a total of 145 observation points. The source of the data is DATASTREAM.

6.5 Estimation Procedure

The parameters Λ, σ_ξ^2, Φ and σ_η^2 can be estimated by QML via the Kalman filter method due to Harvey (1989). The Kalman filter is applied on $\ln(y_t^2)$ to compute the following variables recursively for the sample under consideration:

$$h_{t+1|t} = \Phi h_{t|t-1} + K_t \xi_t, \qquad P_{t+1|t} = \Phi P_{t|t-1} L_t + \sigma_\eta^2,$$

$$\xi_t = \ln(y_t^2) - \Lambda - h_{t|t-1}, \qquad F_t = P_{t|t-1} + \sigma_\xi^2,$$

$$K_t = \Phi P_{t|t-1} F_t^{-1}, \qquad L_t = \Phi - K_t \tag{6.5.1}$$

where $h_{t+1|t} = E_t[h_{t+1}]$ and $P_{t+1|t} = MSE[h_{t+1}]$. A by-product of the filter are the one-step ahead prediction errors, ξ_t, and their corresponding mean square errors, F_t. The next step is to treat ξ_t

and η_t as though they are normal and then use QML, as proposed by Harvey, Ruiz and Shephard (1994). It is also assumed that η_t and ξ_t have finite fourth moments and that the parameters are not on the boundary of the parameter space. The following quasi likelihood is maximised:

$$\ln(L) = -\frac{T}{2}\ln(2\pi) - \frac{T}{2}\sum_{t=1}^{T}\ln(F_t) - \frac{1}{2}\sum_{t=1}^{T}\frac{\xi_t^2}{F_t} \tag{6.5.2}$$

The resulting estimates are consistent and allow asymptotically normal inference.

6.6 Test methods

See chapter three section three for full details of the test methods used. The only difference being that the Ljung-Box test statistics are χ^2 distributed with degrees of freedom adjusted to represent the number of autocorrelations plus one minus the number of hyperparameters in the model. In addition, an adjustment method is required in order to make the log likelihood values of the GARCH type and stochastic volatility models directly comparable. This is because the GARCH type models use returns whereas the stochastic volatility models use mean adjusted squared returns. The transformation, which is based on the normal distribution, as proposed by Hansson and Hördahl (1998) is given by:

$$Lnl(t) = [-\ln(2\pi) - (h_t) - (y_t^2/\exp(h_t))]/2$$

where y_t is the mean adjusted return and h_t is the log-variance obtained from the Kalman filter.

6.7 Modelling Results

Due to the limitations of the STAMP 6.1 package, which is used to obtain the following results, it was not possible to estimate the asymmetric model. Other methods of estimating the asymmetric model involve substantial amounts of programming that are computer intensive. Unfortunately, it was not possible to examine the use of these other methods due to the difficulty involved in their operation. This can handicap the performance of the stochastic volatility model due to the fact that GARCH type models show that a third of the companies have asymmetric volatility. The stochastic volatility model estimates for the thirty-nine FTSE 100 companies, and the index itself, are reported in table 6.1. Overall, the level of volatility persistence is substantially lower than that of the GARCH type models. The volatility persistence level is higher than 0.90 for twenty-six companies and higher than 0.95 for sixteen of the companies examined. This compares to thirty-nine and thirty-six companies respectively for the GARCH model. The average volatility half-life is only four and a half days, as compared to nearly twenty two days for the GARCH/GJR model.

Residual diagnostics for the stochastic volatility models are reported in Table 6.2. The Jarque-Bera statistics once again indicate residual non-normality, although at a substantially reduced level to that of the GARCH type models. The Ljung-Box statistics show that there are substantial serial correlation problems in both the levels and the squares of the residuals. Only eleven companies and the index have no evidence of serial correlation being present in the levels of the residuals. Seven companies did not exhibit serial correlation in the squares of the residuals. A possible explanation for this is that the GARCH(1, 1) model is only the ideal model for twenty two of the companies, the other seventeen companies having higher order models. This is because the stochastic volatility model has similar properties to the GARCH(1, 1) model at higher levels of volatility persistence. Therefore, serial correlation problems can be expected for most of the companies that did not have a GARCH(1, 1) representation. This shows that the stochastic volatility model may have only limited applications to individual stock returns in its standard form. Table 6.3 shows that thirty-four companies are shown to exhibit a Monday effect in the measurement equation. This inherent predictability indicates possible efficiency problems.

Tables 6.4 and 6.5 give the log likelihood and Schwarz criterion values for the stochastic volatility model. The Schwarz criterion is more favourable to models with fewer parameters. The Schwarz criterion favours the stochastic volatility model as compared to the GARCH/GJR model for eighteen companies. The stochastic volatility model improves on the CGARCH/ACGARCH model for seventeen out of thirty-four companies. Overall, the criterion indicates that the stochastic volatility model performs as well as the GARCH type models. This is in spite of the stochastic volatility model generally suffering serial correlation problems. While the standard stochastic volatility model may only have limited relevance for individual stocks, improved asymmetric forms of the stochastic volatility model would outperform GARCH type models.

6.8 Forecasting Procedure

A recursive forecast procedure is used, whereby the in-sample period is extended as the forecast out-of-sample period is moved forward in time. The data is initially partitioned into the in-sample estimation period up to September 7, 1998 and a one-step ahead forecast for the next observation is performed (September 8, 1998 for the daily data and October 5, 1998 for the four-weekly data). The observation for the initial forecasting period is then incorporated into the in-sample period.

For the daily data, the initial model is then re-estimated for the period January 4, 1988 to September 8, 1998 and a one-step ahead forecast is calculated for September 9, 1998. In the case of the four-weekly data, the initial model is re-estimated for the period January 11, 1988 to October 5, 1998 and a one-step ahead forecast is calculated for November 2, 1998. This procedure is repeated until one hundred and twenty daily and six four-weekly one-step ahead forecasts are generated. The one-step ahead forecast of the conditional variance is given by:

$$h_{t+1} = k^2 \exp(h_{t|T})^{\Phi} \tag{6.7.1}$$

where $\exp(h_{t|T})$ is the smoothed estimate of the volatility process. For evaluation purposes, the daily forecasts are put into six sets of twenty one-step ahead forecasts. The four-weekly forecasts are evaluated in one group. The forecast periods are 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively.

6.9 Forecast Evaluation

See chapter four section five for a full exposition of forecast evaluation, methods and criteria adopted.

6.10 Daily Forecast Results

6.10.1 Forecast Appraisal by Forecast sub-periods excluding benchmark models

Table 6.6 reports the forecast error statistics of the thirty-nine FTSE 100 companies and the index itself for the stochastic volatility model. Comparisons are made with the forecast error statistics for the GARCH/GJR and CGARCH/ACGARCH models, which can be seen in Tables 4.3 and 4.4. Table 6.7 reports the best forecast model for the GARCH type and stochastic volatility models. The six forecast periods are 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. Overall, as measured by the average level of volatility, the level of volatility is high in the first and second forecast periods and low in the fourth and sixth forecast periods. The incidence of volatility spikes leads to a deterioration in volatility forecasting performance. The overall impact of volatility spikes can be measured by the difference between the average of the actual and forecast volatilities for the companies as a whole. For the stochastic volatility model, volatility spikes have the greatest impact in the first, second and fifth forecast periods.

6.10.1.1 Sub-period one

In the first forecast period, for comparisons between the stochastic volatility and GARCH/GJR models, the RMSE statistic favours the stochastic volatility model for only nine companies as opposed to twenty-nine, thirty-two and thirty-six companies respectively for the MAE, MedAPE and MedSE forecast error statistics. The MAE, MedAPE and MedSE statistics strongly favour the stochastic volatility model. In contrast, the RMSE statistic strongly favours the GARCH/GJR model. As mentioned in chapter four, the difference arises because the first forecast period is characterised by high levels of volatility together with a high impact of volatility spikes. The RMSE statistic weights greater forecast errors more heavily in the average forecast error penalty. Therefore, the degree of losses associated with higher forecast errors is the critical factor when choosing between the two models. A risk averse investor should choose the GARCH/GJR model over the stochastic volatility model. An investor with a lower degree of risk aversion should use the stochastic volatility model.

Comparisons between the stochastic volatility and CGARCH/ACGARCH models yield similar results. The MAE, MedAPE and MedSE statistics favour the stochastic volatility model over the CGARCH/ACGARCH model. The RMSE statistic favours the CGARCH/ACGARCH model over the stochastic volatility model.

6.10.1.2 Sub-period two

The second forecast period has a high level of volatility although lower than that of the first forecast period. The impact of volatility spikes is still high, although to a lesser extent than the first forecast period. For comparisons between the stochastic volatility model and the GARCH/GJR model, the MAE, MedAPE and MedSE statistics once again strongly favour the stochastic volatility model. The RMSE statistic prefers the GARCH/GJR model although to a lesser extent than in the first forecast period. For comparisons with the CGARCH/ACGARCH model, the MAE, MedAPE and MedSE statistics favour the stochastic volatility model and the RMSE statistic strongly prefers the CGARCH/ACGARCH model. Overall, similar conclusions to the first period can be made. A risk averse investor should use the GARCH/GJR and CGARCH/ACGARCH models over the stochastic volatility model, although the choice is less clear cut than in the first forecast period. This is because the lower level of volatility together with the reduced impact of volatility spikes have reduced the weighting in favour of the GARCH type models. An investor with a lower degree of risk aversion should use the stochastic volatility model.

6.10.1.3 Sub-periods three and four

The third and fourth forecast periods exhibit a lower level of volatility together with a minimal impact of volatility spikes. The MAE, MedAPE and MedSE statistics prefer the stochastic volatility model over the GARCH/GJR and CGARCH/ACGARCH models. The RMSE statistic gives a very weak preference to the stochastic volatility model over the GARCH/GJR model while there is no overall preference between the stochastic volatility and CGARCH/ACGARCH models. Overall, only the most risk averse investor would use the GARCH/GJR and CGARCH/ACGARCH models over the stochastic volatility model in periods of lower volatility. The stochastic volatility model would be the most suitable for the majority of investors.

6.10.1.4 Sub-period five

In contrast to the fourth forecast period, the fifth forecast period is characterised by a higher level of volatility together with volatility spikes having a substantial impact. Consequently, the MAE, MedAPE and MedSE forecast evaluation criteria very strongly favour the stochastic volatility model over the GARCH/GJR and CGARCH/ACGARCH models. The RMSE statistic strongly prefers the GARCH/GJR and CGARCH/ACGARCH models over the stochastic volatility model. As mentioned earlier, this is because the RMSE statistic weights greater forecast errors more heavily in the average forecast error penalty. Which model is best depends on the degree of risk aversion of the individual investor. A risk averse investor should choose the GARCH type models over the stochastic volatility model. An investor who is more risk neutral should use the stochastic volatility model.

6.10.1.5 Sub-period six

Finally, the sixth forecast period has a low level of volatility with volatility spikes having a degree of impact on volatility forecasts. The stochastic volatility model is very strongly preferred to the GARCH/GJR and CGARCH/ACGARCH models by the MAE, MedAPE and MedSE forecast evaluation criteria. The RMSE statistic strongly favours the GARCH type models over the stochastic volatility model. This indicates that the incidence of volatility spikes is the overriding factor in the polarisation of the results for the forecast error statistics. As in the previous forecast period, a risk averse investor should use the GARCH type models while a more risk neutral investor would use the stochastic volatility model.

6.10.1.6 Summary

For the six forecast periods as a whole, a distinct pattern emerges when the volatility preferences of possible investors are taken into account. A risk averse investor should choose the GARCH type models over the stochastic volatility model. An investor who is more risk neutral should use the stochastic volatility model. For lower levels of volatility, such as in the fourth forecast period, only the most risk averse investor should use the GARCH type models over the stochastic volatility model. For the majority of investors the stochastic volatility model would be the most suitable.

6.10.2 Forecast Appraisal by Forecast sub-periods including benchmark models

Table 6.6 reports the forecast error statistics of the thirty-nine FTSE 100 companies and the index itself for the stochastic volatility model. Comparisons are made with the forecast error statistics for the GARCH/GJR, CGARCH/ACGARCH models, historical mean, random walk and exponential smoothing models which can be seen in Tables 4.3 to 4.7. Table 6.8 reports the best forecast model for each forecast evaluation criterion in each of the six forecast periods.

6.10.2.1 Sub-periods one, two and three

The first two periods are characterised by high volatility levels with volatility spikes having a high impact with the third forecast period having a relatively lower volatility level. For the RMSE criterion, the exponential smoothing model is ranked ahead of the GARCH/GJR, CGARCH/ACGARCH and stochastic volatility models. A risk averse investor should choose the exponential smoothing model ahead of the GARCH type and stochastic volatility models. The historical mean model strongly outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria for all bar the MedAPE statistic in forecast period one. In forecast period one the MedAPE statistic prefers the stochastic volatility model for sixteen cases as compared to ten cases for the historical mean model. On balance, a more risk neutral investor should choose the historical mean model for all three forecast periods.

6.10.2.2 Sub-period four

The fourth forecast period exhibits a lower level of volatility as compared to the earlier forecast periods. For the RMSE statistic, the stochastic volatility model is ranked just ahead of the historical mean model. Once again, the MAE, MedAPE and MedSE statistics favour the historical mean model with thirty-four, seventeen and twenty-seven cases respectively. For the median forecast evaluation criteria, the random walk model ranks second, which is to be expected in a period of low volatility. Therefore, a risk averse investor should choose the stochastic volatility model while a more risk neutral investor should choose the historical mean model.

6.10.2.3 Sub-period five

The fifth forecast period has an intermediate level of volatility. The RMSE criterion strongly favours the exponential smoothing model, the GARCH/GJR and CGARCH/ACGARCH models rank second and third respectively. As in the earlier forecast periods, the historical mean model strongly outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. The MedAPE criteria, which gives the lowest penalty to greater forecast errors, ranks the random walk model as second best with twelve companies favouring this forecasting model. The MedSE statistic only favours the random walk model for three companies. This is to be expected, as at intermediate and higher volatility levels, a no change forecast will perform poorly for criteria with higher forecast error penalties. Overall, a risk averse investor should choose the historical mean model and a more risk neutral investor should choose the random walk model.

6.10.2.4 Sub-period six

The sixth forecast period has low volatility levels and the models give a similar forecasting performance to the preceding forecast period. The exponential smoothing model is the best model for the RMSE criterion followed by the CGARCH/ACGARCH model. The historical mean model strongly outperforms the other models for the MAE, MedAPE and MedSE forecast error criteria. Therefore, a risk averse investor should choose the exponential smoothing model and a more risk neutral investor should choose the historical mean model.

6.10.2.5 Summary

For the six forecast periods as a whole, the historical mean model outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. The exponential smoothing model is the best choice of forecasting model for the RMSE statistic for all bar the fourth forecast period, which has the lowest levels of volatility. In the fourth forecast period, the stochastic volatility model ranks as the best for the RMSE statistic. Overall, the GARCH type and stochastic volatility models are outperformed by the benchmark models, therefore, it is not possible to recommend the use of GARCH type and stochastic volatility models for forecasting daily volatility.

6.11 Four-Weekly Forecast Results

Tables 6.9 reports the forecast evaluation criteria for the recursive forecasts of the thirty-nine FTSE 100 companies and the index itself for the stochastic volatility model. Comparisons are made with the forecast error statistics for the GARCH/GJR, CGARCH/ACGARCH, historical mean, random walk and exponential smoothing models which can be seen in Tables 4.8 to 4.12. Table 6.10 reports best forecast model for the GARCH type and stochastic volatility models and Table 6.11 reports the best overall forecast model.

Considering the GARCH type and stochastic volatility models on their own, all the forecast evaluation criteria prefer the GARCH/GJR. Therefore, all investors should choose the GARCH/GJR over the CGARCH/ACGARCH and stochastic volatility models. In contrast to the daily forecasts, the four-weekly forecasts are much more favourable to the GARCH type models when compared against the benchmark models. The GARCH/GJR model ranks as the best model for the RMSE criterion and second best for the MAE, MedAPE and MedSE forecast evaluation criteria. A risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the exponential smoothing model.

6.12 Conclusions

The estimation results show that the stochastic volatility model suffers from substantial serial correlation in the level and the squares of the residuals for most of the companies. A possible reason for this is that the stochastic volatility model has similar properties to that of the GARCH(1, 1) model at higher levels of volatility persistence, which is only the ideal model for twenty-two of the companies. This could indicate that the stochastic volatility model may only have limited applications to individual stock returns in its standard form. The Monday effect is also shown to be a problem for most of the companies. This inherent predictability indicates possible efficiency problems. Nevertheless, the Schwarz criteria indicates that the stochastic volatility model performs as well as the GARCH type models. While the standard stochastic volatility model may only have limited relevance for individual stocks, improved asymmetric forms of the stochastic volatility model would outperform GARCH type models.

For the six forecast periods as a whole, the historical mean model outperforms the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. The exponential smoothing model is the best choice of forecasting model for the RMSE statistic for all bar the fourth forecast period, which has the lowest levels of volatility. In the fourth forecast period, the stochastic volatility model ranks as the best for the RMSE statistic. These results can be explained by the different penalties the forecast evaluation criteria give to higher forecast errors. The RMSE criterion weights greater forecast errors more heavily in the average forecast error penalty. Therefore, a forecast based on historical mean volatility would only perform well in periods when volatility is low. Likewise, a no change forecast of volatility is likely to perform poorly when judged by a high penalty forecast error criterion. The MAE, MedAPE and MedSE criteria have much lower penalties for greater forecast errors. The historical mean model is then likely to perform particularly well, as on average the historical volatility level will be near the actual volatility. Overall, the GARCH type and stochastic volatility models are outperformed by the benchmark models, therefore, it is not possible to recommend the use of GARCH type and stochastic volatility models for forecasting daily volatility. In contrast to the daily forecasts, the four-weekly forecasts are much more favourable to the GARCH type models when compared against the benchmark models. The GARCH/GJR model ranks as the best model for the RMSE criterion and second best for the MAE, MedAPE and MedSE forecast evaluation criteria. A risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the exponential smoothing model.

Chapter 7 - Stock Market Volatility

7.1 Introduction

So far, the analysis has concentrated on the FTSE 100 index and thirty-nine of its constituent stocks. Approximately one third of the stocks show some measure of volatility asymmetry and 85 percent of the stocks have volatility components. In terms of modelling ability, the GJR model outperforms the GARCH model. The CGARCH/ACGARCH model gives a useful break down of volatility but it does not sufficiently improve on the GARCH/GJR model. The stochastic volatility model performs on a par with the GARCH type models. In forecasting terms, the GARCH type and stochastic volatility models are outperformed by the benchmark models, therefore, it is not possible to recommend the use of the GARCH type and stochastic volatility models for forecasting daily volatility. For the daily forecasts as a whole, a risk averse investor should choose the exponential smoothing model while a more risk neutral investor should choose the historical mean model. The four-weekly forecasts are much more favourable to the GARCH type models when compared against the benchmark models. The GARCH/GJR model ranks as the best model for the RMSE criterion and second best for the other forecast evaluation criteria. A risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the exponential smoothing model. These conclusions may only be restricted to U.K. based stocks. Therefore, in order to complete a broader analysis of stock market volatility, a number of international stock indices will also be examined. In particular, six major international indices and four emerging market stock market indices are examined. This will also enable a comparison of the characteristics of stock market volatility between the major indices and the emerging market indices.

The remainder of the chapter is organised as follows. Section two gives details about the volatility models together with empirical evidence on their modelling and forecasting ability. Section three contains information about the data set and the estimation procedures used. Section four gives the estimation results. Section five details the forecasting procedure while sections six and seven give the forecasting models and the evaluation methods used. Sections eight and nine contain the forecast results. Finally, section ten offers some concluding remarks.

7.2 Models

The models estimated are only briefly restated here. A fuller exposition of the details of the following models is given in chapter two, section two and chapter six, section two.

7.2.1 GARCH Model

The conditional mean model as with all the following GARCH type models is an AR(1) model.

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{7.2.1}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{7.2.2}$$

In order to examine the Monday effect, the conditional mean equation is modified by the inclusion of a dummy variable term M_t, such that $M_t = 1$ when the day of the week is Monday and zero otherwise. The conditional mean equation becomes:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t \tag{7.2.3}$$

7.2.2 GJR Model

The 'leverage effect' is captured by modifying the GARCH model via the inclusion of a dummy variable term D_{t-1}, such that $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise.

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{7.2.1}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} \tag{7.2.4}$$

A positive value of γ indicates that the 'leverage effect' exists.

7.2.3 CGARCH Model

The conditional variance is decomposed into a permanent and a transitory component, which is mean reverting towards the trend component. The two components help to explain the long-run and short-run movements of stock market volatility. The time-varying permanent component acknowledges the possibility that long-run volatility is not constant. The model is given by:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \tag{7.2.1}$$

$$h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1} - q_{t-1}) \tag{7.2.5}$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1}) \tag{7.2.6}$$

where q_t is the permanent component of stock market volatility.

7.2.4 ACGARCH Model

The short-run leverage effect is examined by the inclusion of a dummy variable term D_{t-1}, such that $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The long-run leverage effect should be zero as a firm is able to adjust its capital structure in the long-run. The component model becomes:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t \qquad (7.2.1)$$

$$h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) \qquad (7.2.7)$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1}) + \delta_l(D_{t-1}\epsilon_{t-1}^2 - 0.5h_{t-1}) \qquad (7.2.8)$$

7.2.5 Stochastic Volatility Model

The conditional variance is specified as an unobserved component or latent stochastic process. Let y_t denote the continuous return of an asset corrected for the unconditional mean. The state space model can be written as:

$$\ln(y_t^2) = \Lambda + h_t + \xi_t \qquad (7.2.9)$$

$$h_{t+1} = \Phi h_t + \eta_t \qquad (7.2.10)$$

where $\Lambda = \ln(k^2) + E_t[\ln(Z_t^2)]$ and $\ln(k^2) = (\frac{\delta}{1 - \Phi})$. Equation (7.2.9) is the measurement equation and (7.2.10) is the transition equation. The Monday effect can be examined by modifying the measurement equation via the inclusion of a dummy variable term M_t, such that $M_t = 1$ when the day of the week is Monday and zero otherwise. The measurement equation becomes:

$$\ln(y_t^2) = \Lambda + \lambda_d M_t + h_t + \xi_t \qquad (7.2.11)$$

7.2.6 Empirical Evidence

See chapter two, section two for a guide on the modelling ability of GARCH type models. Evidence on the forecasting ability of GARCH type models is given in chapter four, section two. Chapter five, section three contains a full exposition on the modelling and forecasting ability of stochastic volatility models.

7.3 Data and Estimation Procedure

The source of the data is DATASTREAM. The data set contains the daily values of ten international stock indices. The major stock indices are selected on the basis that they are generally acknowledged to be the ones of most importance in terms of market size. Six major stock indices are used: the French CAC 40, German DAX, Japanese Nikkei 225, U.S. Dow Jones Industrial Average (DJIA), U.S. Standard & Poor 500 (S & P 500) and the U.S. NASDAQ Composite. For a comparison measure, emerging market indices form four emerging market stock indices are also used: the Hong Kong Hang Seng, Singaporean Singapore Straits Times (SST), South Korean Korea SE Composite (KSE) and the Argentinian Merval. These are selected on the basis that they have well behaved conditional mean equations. With the exception of the DAX, Nikkei 225 and Merval indices, the data covers the period January 4, 1988 to February 22, 1999, giving a total of 2,906 observation points. The starting dates for the DAX, Nikkei 225 and the Merval indices are July 1, 1991, January 4, 1991 and August 2, 1993 respectively. This gives a total of 1,996, 2,122 and 1,451 observations respectively. The shorter sample periods are due to the construction of new indices at the given dates. Summary statistics for the returns data are shown in Table 7.1. All the returns exhibit excess kurtosis, with the Hang Seng and SST indices having particularly high levels of excess kurtosis. This leads to all of the stock indices having a significant Jarque-Bera test statistic and thereby rejecting the null hypothesis of normality. For an estimation procedure and the test methods used in estimating GARCH type models, see chapter three, sections two and three. An estimation procedure for stochastic volatility models is given in chapter six, section five.

7.4 Estimation Results

7.4.1 GARCH/GJR Model Results

The AR(1)-GARCH/GJR(p, q) model estimates for the ten stock indices are reported in Table 7.2. The positive values of the ARCH(1) and GARCH(1) coefficients show that volatility is positively related to shocks to the conditional mean and to previous volatility levels. All eight of the indices with an AR(1) term in the mean equation, have significantly positive AR(1) coefficients. The return autocorrelation varies from 0.0385 for the S&P 500 to 0.2126 for SST, which is similar to the levels of return autocorrelation found in other studies. Overall, the emerging market indices have a higher positive returns autocorrelation than the major stock indices. This is compatible with the idea that emerging markets having a lower level of market efficiency. The results are consistent with negative feedback trading strategies such as profit taking and value trading (buying after price falls). Nine of the indices have significant volatility asymmetry that is consistent with the leverage effect hypothesis. A negative shock raises conditional variance by between 6.6 percent (U.S. S&P 500) and 17.6 percent (Merval) in comparison with an equivalent positive shock

As can be seen from Table 7.3, the estimated level of volatility persistence is high for all the stock indices. The persistence level is higher than 0.90 for all the stock indices and higher than

0.95 for six indices. Indeed, the limiting IGARCH case cannot be ruled out for three of the indices. Three of the four of the emerging market indices do not reject the null hypothesis of an integrated variance. Therefore, shocks to the mean would persist indefinitely in conditioning the future conditional variance for three of the emerging market indices.

Residual diagnostics for the AR(1)-GARCH/GJR(p, q) models are reported in Table 7.4. The continued existence of excess kurtosis, as indicated by a significant Jarque-Bera statistic, points to the correct use of Bollerslev-Wooldridge robust standard errors. The Ljung-Box statistics indicate that only the Hang Seng index shows any sign of serial dependence in the levels of the standardised residuals, the Q_5 statistic being significant at the 5 percent level. In the squares of the standardised residuals, the Q_{10}^2 statistic for the KSE index is significant at the 5 percent level. The ARCH -LM test also indicates variance misspecification at the tenth lag for the KSE index. The relatively long lag length can lead to the possibility that the results are spurious.

7.4.2 CGARCH/ACGARCH Model Results

CGARCH/ACGARCH model estimates for six indices are reported in Table 7.5. The remaining indices have insignificant transitory component terms, therefore, they reduce down to the standard GARCH/GJR model. Estimates of the autoregressive component are significant for all the indices, and higher than 0.95 for all bar the SST and DAX indices. Compared with the GARCH/GJR models, allowing for a transitory volatility component increases the volatility persistence for all except the DAX and DJIA indices. Consequently, Table 7.6 shows that the null hypothesis of integration in the permanent component can be rejected for only the DAX index at the 5 percent significance level. The SST index has an insignificant impact of transitory shocks. Three of the indices have negative persistence for the transitory component of volatility. The remaining indices, S&P 500, NASDAQ and KSE, have a half-life of a shock to the transitory component that is more than ten times less than the half-life of a shock to the permanent component. The DAX, DJIA, SST and Hang Seng indices fail to satisfy the conditions for non negativity of the conditional variance in all circumstances. However, as seen from figures 7.1 to 7.4, the conditional standard deviation remains positive at all times. Therefore, the failure to pass the non-negativity conditions will only affect out of sample measurements.

The DJIA and KSE indices have significant transitory component volatility asymmetry. Referring to the final column of Table 7.6. The estimates show that a negative shock raises transitory conditional variance by 11.9 percent for the DJIA index and 8.1 percent for the KSE index in comparison with an equivalent positive shock. Neither index has a significant time variation in the permanent component. The impact of positive shocks to the transitory component is insignificant for both indices, while only the KSE index has a significant impact for negative shocks. Therefore, the KSE index has negative shocks dominating the effects on the transitory component.

Residual diagnostics for the CGARCH/ACGARCH models are reported in Table 7.7. The Jarque-Bera test statistics continue to reject the null hypothesis of normality, showing the correct use of Bollerslev-Wooldridge robust standard errors. The Ljung-Box statistics show that only the Hang Seng index has serial correlation in the levels of the standardised residuals, the Q_5 statistic being significant at the 5 percent level. In the squares of the standardised residuals, the Q_{10}^2

statistic, together with the corresponding ARCH-LM statistic, are significant at the 5 percent level for the KSE index. This can be a spurious result, rather than evidence of conditional variance misspecification, due to the longer lag length involved.

7.4.3 Stochastic Volatility Model Results

The stochastic volatility model estimates for the ten indices are reported in Table 7.8. Overall, the level of volatility persistence is higher than that of the GARCH/GJR models. The average volatility half-life is just over seventeen days, as compared to fifteen days for the GARCH/GJR model. Also, the emerging market indices generally have a lower level of volatility persistence than the major stock indices.

Residual diagnostics for the stochastic volatility models are reported in Tables 7.9. The Jarque Bera statistics indicate residual non normality, although at a substantially reduced level relative to the GARCH type models. The Ljung-Box statistics indicate that there are serial correlation problems in both the levels and the squares of the residuals. The DJIA, NASDAQ and the Hang Seng suffer from serial correlation in the levels of the residuals. In the squares of the residuals, four indices show evidence of conditional variance misspecification. This leaves only the CAC 40, DAX, S&P 500 and Merval having no serial correlation problems. Extending the standard form of the model to an asymmetric specification should reduce the conditional variance misspecification problem.

7.4.4 Monday Effect Results

Model estimates for the AR(1)-GARCH/GJR(p, q) models including the Monday effect are reported in Table 7.10. The results are similar to those of the standard GARCH/GJR models. Wald tests indicate that the null hypothesis that the Monday effect does not exist can be rejected for five indices. The dummy variable terms indicate that the stock return on a Monday is lower by between 0.10 and 0.25 percent. This level of reduced returns is consistent with the Monday effect results for individual British stocks.

Table 7.11 reports model estimates for the AR(1)-CGARCH/ACGARCH models including the Monday effect. Three of the five indices identified by the GARCH/GJR model have significant component model terms, the remainder reduce down to the Monday effect GARCH/GJR model. The Monday effect reduces returns by between 0.13 and 0.23 percent. Referring to Table 7.12, the stochastic volatility model Monday effect results indicate that four indices are shown to exhibit a Monday effect. As the equation is set in terms of mean adjusted squared returns, the results are not directly comparable to the GARCH type models. Overall, of the five indices that have a Monday effect GARCH/GJR representation, the Monday effect still remains after taking leverage effects and volatility components into account. Obviously, this brings into question market efficiency in that there is a possibility of profitable trading rules existing. Against this, the effect is small and transaction costs need to be taken into account.

7.4.6 Model Comparisons

Tables 7.13 and 7.14 give the log likelihood and Schwarz criterion values for the GARCH, GJR, CGARCH, ACGARCH and stochastic volatility (SV) models. The Schwarz criterion is more favourable to models with fewer parameters. The Schwarz criterion favours the GJR model over the GARCH model for all nine indices that can be represented by the GJR model. For the smaller sample of six indices that have an CGARCH/ACGARCH representation, the GARCH/GJR model is superior in all cases. Therefore, the CGARCH/ACGARCH model is only of limited relevance for the indices as it is comprehensively outperformed by a simpler model.

For the individual British stocks, the stochastic volatility model performed on a par with the GARCH type models while the GARCH/GJR model is favoured by seven of the indices. The CGARCH/ACGARCH model outperforms the stochastic volatility model for four of the six indices with an CGARCH/ACGARCH representation. This seemingly poor modelling performance is countered by the fact that the stochastic volatility model is the best model for three indices with the GARCH/GJR model being the best model for the remaining indices. Taking the earlier estimation results into account, the model with the best overall modelling performance is the GARCH/GJR model. This is followed by the stochastic volatility model with the CGARCH/ACGARCH model trailing further behind.

7.5 Forecasting Procedure

A recursive forecast procedure is used, whereby the in-sample period is extended as the forecast out-of-sample period is moved forward in time. The data is initially partitioned into the in-sample estimation period up to September 7, 1998 and a one-step ahead forecast for the next observation is performed (September 8, 1998 for the daily data and October 5, 1998 for the four-weekly data). The observation for the initial forecasting period is then incorporated into the in-sample period. For the daily data, the initial model is then re-estimated for the period January 4, 1988 to September 8, 1998 and a one-step ahead forecast is calculated for September 9, 1998. In the case of the four-weekly data, the initial model is re-estimated for the period January 11, 1988 to

October 5, 1998 and a one-step ahead forecast is calculated for November 2, 1998. This procedure is repeated until one hundred and twenty daily and six four-weekly one-step ahead volatility forecasts are generated. For evaluation purposes, the daily forecasts are put into six sets of twenty one-step ahead forecasts while the four-weekly forecasts are evaluated as one group. The forecast periods are 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively.

7.6 Volatility Forecasting Models

7.6.1 GARCH Model

The GARCH one-step ahead volatility forecast is expressed as

$$h_{t+1} = \omega_T + \sum_{i=1}^{q} \alpha_{i,T} \epsilon^2_{t-i+1} + \sum_{i=1}^{p} \beta_{i,T} h_{t-i+1} \; ; \qquad t = T, T+1, \ldots, T+\tau-1 \tag{7.6.1}$$

for $t = T, T+1, \ldots, T+\tau-1$.

7.6.2 GJR Model

The GJR one-step ahead volatility forecast is expressed as:

$$h_{t+1} = \omega_T + \sum_{i=1}^{q} \alpha_{i,T} \epsilon^2_{t-i+1} + \sum_{i=1}^{p} \beta_{i,T} h_{t-i+1} + \gamma_t \epsilon_t^2 D_t \tag{7.6.2}$$

for $t = T, T+1, \ldots, T+\tau-1$.

7.6.3 CGARCH Model

The CGARCH one-step ahead volatility forecast is generated by using:

$$h_{t+1} = q_{t+1} + \alpha(\epsilon_t^2 - q_t) + \beta(h_t - q_t) \tag{7.6.3}$$

$$q_{t+1} = \omega + \rho q_t + \phi(\epsilon_t^2 - h_t) \tag{7.6.4}$$

for $t = T, T + 1, \ldots, T + \tau - 1.$

7.6.4 ACGARCH Model

The ACGARCH one-step ahead volatility forecast is expressed as:

$$h_{t+1} = q_{t+1} + \alpha(\epsilon_t^2 - q_t) + \delta_s(D_t\epsilon_t^2 - 0.5q_t) + \beta(h_t - q_t) \tag{7.6.5}$$

$$q_{t+1} = \omega + \rho q_t + \phi(\epsilon_t^2 - h_t) + \delta_l(D_t\epsilon_t^2 - 0.5h_t) \tag{7.6.6}$$

for $t = T, T + 1, \ldots, T + \tau - 1.$

7.6.5 Stochastic volatility Model

The stochastic volatility one-step ahead volatility forecast is given by:

$$h_{t+1} = k^2\exp(h_{t|T})^{\Phi} \tag{7.6.7}$$

for $t = T, T + 1, \ldots, T + \tau - 1.$

7.7 Forecast Evaluation

Forecasting ability is evaluated by using the root mean square error (RMSE), mean absolute error (MAE), median absolute percentage error (MedAPE) and the median squared error (MedSE), which are defined as follows:

$$RMSE = \sqrt{\frac{1}{\tau}\sum_{t=T+1}^{T+\tau}(h_t - s_t^2)^2} \tag{7.7.1}$$

$$MAE = \frac{1}{\tau}\sum_{t=T+1}^{T+\tau}|h_t - s_t^2| \tag{7.7.2}$$

$$MedAPE = median\left(\left|\frac{h_t - s_t^2}{s_t^2}\right|\right) \tag{7.7.3}$$

$$MedSE = median((h_t - s_t^2)^2) \tag{7.7.4}$$

7.8 Daily Forecast Results

7.8.1 Forecast Appraisal by Forecast sub-periods excluding benchmark models

Tables 7.15 to 7.17 report the forecast error statistics for the volatility forecasts of the ten indices for the GARCH/GJR, CGARCH/ACGARCH and stochastic volatility models. Table 7.21 reports the best forecast model for the GARCH type and stochastic volatility models. The six forecast periods are 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. Overall, as measured by the average level of volatility, the level of volatility is high in the first and second forecast periods and low in the third and sixth forecast periods. The profile of volatility is similar to that of the individual British stocks, except that volatility is relatively lower in the third forecast period instead of the fourth forecast period. The overall impact of volatility spikes, as measured by the difference between the average of the actual and forecast volatilities, is highest in the first, second and fifth forecast periods.

7.8.1.1 Sub-period one

The first forecast period is characterized by high levels of volatility together with a high impact of volatility spikes. For comparisons between the stochastic volatility and GARCH/GJR models, the MAE, MedAPE and MedSE forecast evaluation criteria favour the stochastic volatility model for five, six and nine indices respectively. In contrast, the RMSE forecast evaluation criterion favours the SV model for only two indices. The RMSE statistic rates the GARCH/GJR model as the best overall model for seven indices as compared to the MAE, MedAPE and MedSE statistics that rate the GARCH/GJR model as the best for five, two and one index respectively. The stochastic volatility model is the best overall model for four, six and eight indices respectively when judged by the MAE, MedAPE and MedSE forecast evaluation criteria. As is the case for the individual stocks, in periods of higher volatility, the degree of losses associated with higher forecast errors is the critical factor when choosing between models. The RMSE statistic weights greater forecast errors more heavily in the in the average forecast error penalty. A more risk averse investor should align their choices with that of the RMSE statistic and choose the GARCH/GJR model. Investors with a lower degree of risk aversion should choose the stochastic volatility model and base their decisions on the MAE, MedAPE and MedSE forecast error statistics. There is more of an even balance between the forecasting performances of the stochastic volatility and CGARCH/ACGARCH models. Nevertheless, a risk averse investor should choose the CGARCH/ACGARCH model over the stochastic volatility model while a more risk neutral investor should choose the stochastic volatility model.

7.8.1.2 Sub-period two

The second forecast period has a high level of volatility with volatility spikes having a large impact, although the volatility is at a lower level than that of the first forecast period. Compared to the first forecast period, the stochastic volatility model gives a poorer forecast performance. The stochastic volatility model is the best overall model for three, five, three and four indices respectively when judged by the RMSE, MAE, MedAPE and MedSE forecast evaluation criteria. The lower level of volatility leads to a decline in the relative forecasting performance of the stochastic volatility model. All the statistics except the MAE favour the GARCH/GJR model over the stochastic volatility model, the MAE statistic gives an even split between the models.

Comparing the stochastic volatility and CGARCH/ACGARCH models, the MAE, MedAPE and MedSE statistics favour the stochastic volatility model while the RMSE statistic prefers the CGARCH/ACGARCH model. A risk averse investor would choose the CGARCH/ACGARCH model over the stochastic volatility model while a more risk neutral investor should choose the stochastic volatility model. Against the GARCH/GJR model, the CGARCH/ACGARCH model gives a poor forecast performance when judged by the MAE, MedAPE and MedSE forecast error statistics. The RMSE statistic favours the CGARCH/ACGARCH model for three indices out of the six indices which have an CGARCH/ACGARCH representation. Overall, the GARCH/GJR model is the best choice of forecast model for all investors in the second forecast period.

7.8.1.3 Sub-period three

The third forecast period has a much lower level of volatility than the preceding periods. The GARCH/GJR model strongly outperforms the other models for all the forecast error statistics. Therefore, all investors should base their decisions on the GARCH/GJR model.

7.8.1.4 Sub-period four

The fourth forecast period has a low level of volatility, although at a relatively higher level than the third forecast period. The GARCH/GJR model outperforms the stochastic volatility model for three forecast error statistics. The RMSE, MAE and MedSE statistics favour the GARCH/GJR model while the MedAPE statistic gives no overall preference. The CGARCH/ACGARCH model gives a comparatively weak forecasting performance against all the models except the stochastic volatility model. The GARCH/GJR model is the best choice of forecast model for investors regardless of their degree of risk aversion.

7.8.1.5 Sub-period five

The fifth forecast period is characterised by an intermediate level of volatility together with a high incidence of volatility spikes. For comparisons between the stochastic volatility and GARCH/GJR models, the RMSE and MedAPE forecast evaluation criteria prefer the GARCH/GJR model for six and seven indices respectively. The MAE and MedSE statistics are evenly split between the two models. The CGARCH/ACGARCH model performs particularly well against the GARCH/GJR model for the RMSE statistic, in contrast to the other statistics where it is comprehensively beaten. Overall, an investor should choose the GARCH/GJR model whatever their degree of risk preference.

7.8.1.6 Sub-period six

Finally, the sixth forecast period is characterized by a low overall level of volatility. For comparisons between the GARCH/GJR and stochastic volatility models, the RMSE, MAE and MedAPE statistics have no overall preference between the models. The MedSE statistic prefers the GARCH/GJR model to the stochastic volatility model. Nevertheless, the stochastic volatility model gives the best overall performance for more indices than the GARCH/GJR model when judged by the MedAPE statistic. The MedAPE statistic rates the stochastic volatility model as the best model for five indices while the RMSE, MAE and MedSE rate the model as the best for four indices. The CGARCH/ACGARCH model performs equally as well as the stochastic volatility model for direct comparisons between the two models. On balance, as is the case for the four preceding forecast periods, the GARCH/GJR model should be the choice of all investors regardless of their degree of risk preference.

7.8.1.7 Summary

For the six forecast periods as a whole, the GARCH/GJR is the best, with it being the optimal choice of all investors for the second to sixth forecast periods. Only in the first forecast period, which is characterised by high volatility and a high incidence of volatility spikes, is the stochastic volatility model the best choice for investors who have a lower degree of risk aversion. The GARCH/GJR model still remains the best choice for investors who are risk averse.

7.8.2 Forecast Appraisal by Forecast sub-periods including benchmark models

Tables 7.15 to 7.20 report the forecast error statistics for the volatility forecasts of the ten indices for the GARCH/GJR, CGARCH/ACGARCH, stochastic volatility, historical mean, random walk and exponential smoothing models. Table 7.22 reports the best overall forecast model for each forecast evaluation criterion in each of the six forecast periods.

7.8.2.1 Sub-period one

The first forecast period is characterised by the highest volatility levels together with a high impact of volatility spikes. The RMSE statistic ranks the GARCH/GJR model as the best model for six indices compared to four indices for the exponential smoothing model while the MAE statistic prefers the GARCH/GJR and stochastic volatility models for four indices each. The MedAPE and MedSE forecast evaluation criteria strongly favour the stochastic volatility model over the other models. Therefore, a risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the stochastic volatility model.

7.8.2.2 Sub-period two

The second forecast period also has high volatility levels, although they are lower than that seen in the first forecast period. The RMSE forecast evaluation criterion ranks the GARCH/GJR as the best followed by the stochastic volatility model, the GARCH/GJR model is preferred for four indices while the stochastic volatility model is favoured for three indices. This preference is reversed for the MAE statistic, the stochastic volatility model is the best model for five indices as opposed to four indices for the GARCH/GJR model. The MedAPE and MedSE statistics rank the random walk model as the best, followed by the GARCH/GJR and stochastic volatility models. Therefore, a risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the stochastic volatility model.

7.8.2.3 Sub-periods three and four

These forecast periods have relatively lower volatility levels than the first two forecast periods. The RMSE and MAE statistics favour the GARCH/GJR model while the MedAPE and MedSE statistics prefer the random walk model. As in forecast sub-period two, a risk averse investor should choose the GARCH/GJR model while a more risk neutral investor should choose the random walk model.

7.8.2.4 Sub-period five

The fifth forecast period is characterised by volatility spikes having high impact levels. The RMSE statistic favours the historical mean model for three indices as opposed to two indices for the exponential smoothing, CGARCH/ACGARCH and stochastic volatility models while the GARCH/GJR model is preferred for one index. The MAE statistic favours the GARCH/GJR and stochastic volatility models for five indices each. Given that a direct comparison between the GARCH/GJR and stochastic volatility models favours the GARCH/GJR model for the RMSE statistic, a risk averse investor should choose the GARCH/GJR model. For a more risk neutral investor, the performance of the random walk and GARCH/GJR models are more evenly balanced. A direct comparison between the two models reveals that the MedAPE statistic favours the random walk model for six indices as compared to four indices for the GARCH/GJR model. The MedSE statistic prefers the GARCH/GJR model for seven indices while the random walk model is favoured for only three indices. Overall, as the MedAPE statistic is more aligned with the preferences of a more risk neutral investor, the random walk model is the best choice for a more risk neutral investor.

7.8.2.5 Sub-period six

The sixth forecast period has low volatility levels. The GARCH/GJR and stochastic volatility models are ranked jointly as the best forecasting models for the RMSE and MAE statistics. For consistency with the earlier periods, a risk averse investor should choose the GARCH/GJR model. The MedAPE and MedSE statistics prefer the random walk model over the other models. Therefore, a more risk neutral investor should choose the random walk model.

7.8.2.6 Summary

Overall, the GARCH/GJR model should be the choice of risk averse investors while a more risk neutral investor should choose the random walk model for all except the first forecast period. In the first forecast period, which is characterised by the highest volatility levels, a more risk neutral investor should choose the stochastic volatility model.

7.9 Four-Weekly Forecast Results

Tables 7.23 to 7.28 report the forecast error statistics for the volatility forecasts of the ten indices for the GARCH/GJR, CGARCH/ACGARCH, stochastic volatility, historical mean, random walk and exponential smoothing models. Table 7.29 reports the best forecast model for the GARCH type and stochastic volatility models and Table 7.30 reports the best overall forecast model. Considering the GARCH type and stochastic volatility models on their own, the RMSE and MAE statistics rank the GARCH/GJR and stochastic volatility models as the best forecasting models for four indices each. Direct comparisons between the GARCH/GJR and stochastic volatility models reveal that the RMSE statistic is evenly split between the two models while the MAE statistic favours the GARCH/GJR model. Likewise, the MedAPE and MedSE statistics strongly favour the

GARCH/GJR model. Therefore, all investors should choose the GARCH/GJR model over the CGARCH/ACGARCH and stochastic volatility models. Comparisons against the benchmark models show that the GARCH/GJR model is ranked as the best forecasting model for the RMSE and MAE forecast evaluation criteria. Overall, MedAPE and MedSE statistics rank the CGARCH/ACGARCH, stochastic volatility and historical mean models as the best. Therefore, a risk averse investor should use the GARCH/GJR model while for a more risk neutral investor the CGARCH/ACGARCH, stochastic volatility and historical mean models are equally valid choices.

7.10 Conclusions

In terms of modelling performance, the GARCH /GJR model is favoured by seven of the indices while the stochastic volatility model is preferred by the remaining three indices. The CGARCH/ACGARCH model outperforms the stochastic volatility model for four of the six indices with an CGARCH/ACGARCH representation. Therefore, the model with the best overall modelling performance is the GARCH/GJR model. This is followed by the stochastic volatility model with the CGARCH/ACGARCH model trailing further behind.

For the daily volatility forecasts, the GARCH/GJR model should be the choice of risk averse investors while a more risk neutral investor should choose the random walk model for all except the first forecast period. In the first forecast period, which is characterised by the highest volatility levels, a more risk neutral investor should choose the stochastic volatility model. For the four-weekly forecasts, a risk averse investor should use the GARCH/GJR model while for a more risk neutral investor the CGARCH/ACGARCH, stochastic volatility and historical mean models are equally valid choices.

Chapter 8 - Conclusions

The objective of the thesis was to give a detailed analysis of the volatility of stock and stock market indices for a ten year period between 1988 and 1998. In particular, a comparison of the modelling and forecasting ability of GARCH type and stochastic volatility models was undertaken. The volatility-volume relationship was also considered, that is, whether GARCH effects in stock returns can be explained by temporal dependence in the volume of trade. The volatility-volume analysis was also extended to CGARCH models.

The volatility properties of six major and four emerging stock market indices were also examined. This allowed a comparison of the volatility properties of the individual stocks with those of the indices. It gave the opportunity to see whether the findings about the volatility of U.K. based stocks could be extended to the international stock markets. It also enabled a comparison of the characteristics of stock market volatility between the major indices and the emerging market indices.

The standard GARCH model can be improved in a number of ways to give a better representation of stock returns for the FTSE 100 companies examined. GARCH models are linear in the conditional variance, therefore, they cannot model phenomenon such as the 'leverage effect', which is the negative correlation between volatility and past returns. The GJR model incorporates a non-linear conditional variance in quadratic form. This resulted in improved modelling ability, when judged by information criteria, for the companies which had significant asymmetry terms. Another area of potential improvement is the permanent transitory volatility decomposition. This is because the GARCH and GJR models assume homogeneity of the price discovery process and are unable to capture the effects of short and long-run volatility components. Despite more accurately characterising volatility, the CGARCH model did not represent an improvement over the GARCH model in terms of modelling ability. The ACGARCH model improved upon the CGARCH model for the six companies where its use was valid.

Overall, the GJR and ACGARCH models identified approximately one third of the companies as supporting the 'leverage effect'. Possible reasons for the widespread existence of the 'leverage effect' include asymmetric volatility in the index resulting from the asymmetric volatility found in its constituent companies, market wide 'leverage effects' inducing asymmetric volatility in the companies and 'churning' of the index composition introducing sample specific effects.

The stochastic volatility model suffered from substantial serial correlation in the levels and the squares of the residuals for most of the companies and for six of the indices. A possible reason for this is that the stochastic volatility model has similar properties to that of the GARCH(1, 1) model at higher levels of volatility persistence, which is only the ideal model for twenty-two of the companies. Nevertheless, the Schwarz criterion indicated that the stochastic volatility model performed as well as the GARCH type models for the FTSE 100 companies. In the case of the indices, the GARCH/GJR model is preferred to the stochastic volatility model. The CGARCH/ACGARCH model outperformed the stochastic volatility model for four of the six indices with a CGARCH/ACGARCH representation. Taking the estimation results into account, the model with the best overall performance is the

GARCH/GJR model. This was followed by the stochastic volatility model with the CGARCH/ACGARCH model trailing further behind. This conclusion is somewhat tempered by the fact that I was unable to carry out estimation of asymmetric stochastic volatility models. The increased level of computing power together with the introduction of new computer programs would allow a more thorough examination of asymmetric stochastic volatility models.

All the stock return autocorrelations were found to be positive, this is consistent with negative feedback trading strategies such as value trading (buying after price falls) and profit taking. The return autocorrelation was found to vary from 0.01 to 0.16 while the index return autocorrelations varied from 0.03 to 0.21. This is similar to the levels of return autocorrelation found in other studies. This can have implications about the efficiency of the stock market due to the predictable patterns in stock returns. Nevertheless, taking advantage of the predictable return patterns involves an element of risk which can account for the stock return autocorrelation pattern. This is because a certain risk premium would be needed in order to take on the risk.

The GARCH/GJR volume results showed that serial dependence in the volume of trade only explained some but not all of the volatility persistence of the GARCH model. This is consistent with the findings of a number of more recent papers examining the volatility-volume relationship. As the GARCH effects did not vanish with the introduction of volume of trade into the variance equation, this provided strong evidence against the MDH. In an extension of the current work on the volatility-volume relationship, the analysis was extended to CGARCH/ACGARCH models with volume in the temporary component. The

CGARCH/ACGARCH volume results provided little support for the MDH. Only the lagged volume CGARCH/ACGARCH results provided some consistent support for the MDH. Nevertheless, companies that supported the MDH were out numbered four to one by companies providing evidence against the MDH. Overall, the evidence supported the idea that the MDH only explained some of the GARCH effects and that there may be other variables beside volume that contribute to the heteroscedasticity in market returns.

The results for the daily volatility forecasts of the individual stocks are consistent with my original hypothesis that the inherent noise in the return generating process would lead to the GARCH type models giving a relatively poor forecast of volatility. The historical mean model outperformed the other models for the MAE, MedAPE and MedSE forecast evaluation criteria. The exponential smoothing model was the best choice of forecasting model for the RMSE statistic for all bar the fourth forecast period, which had the lowest levels of volatility. In the fourth forecast period, the stochastic volatility model was ranked as the best for the RMSE statistic. These results can be explained by the different penalties the forecast evaluation criteria give to higher forecast errors. The RMSE criterion weights greater forecast errors more heavily in the average forecast error penalty. Therefore, a forecast based on historical mean volatility would only perform well in periods when volatility is low. The MAE, MedAPE and MedSE criteria have much lower penalties for greater forecast errors. The historical mean model is then likely to perform particularly well, as on average the historical volatility level will be near the actual volatility. Overall, the GARCH type and stochastic volatility models were outperformed by the benchmark models, therefore, it is not possible to recommend the use of GARCH type and stochastic volatility models for forecasting daily volatility.

In contrast to the daily forecasts, the four-weekly forecasts were much more favourable to the GARCH type models when compared against the benchmark models. This is consistent with my initial hypothesis that GARCH type volatility forecasts would perform relatively better due to the noise in the return generating process being reduced by using daily data to evaluate the true volatility. The GARCH/GJR model ranked as the best model for the RMSE criterion and second best for the MAE, MedAPE and MedSE forecast evaluation criteria. A risk averse investor should have chosen the GARCH/GJR model while a more risk neutral investor should have chosen the exponential smoothing model.

For the daily volatility forecasts of the indices, the GARCH/GJR model should have been the choice of risk averse investors while a more risk neutral investor should have chosen the random walk model for all except the first forecast period. In the first forecast period, which is characterised by the highest volatility levels, a more risk neutral investor should have chosen the stochastic volatility model. The relatively better performance of the daily volatility forecasts for the indices is due to the fact that the large numbers of constituent stocks in an index tend to average out the noise in the return generating process of the individual stocks. The four-weekly forecasts supported the idea that a risk averse investor should have used the GARCH/GJR model. For an investor who is more risk neutral the choice was less clear cut, with the CGARCH/ACGARCH, stochastic volatility and historical mean models proving equally valid choices.

An avenue of further research is provided by GARCH type models that could possibly improve on the models already examined. For example, fractionally integrated GARCH models could be used due to the high incidence of stocks where the limiting case of an

IGARCH model can not be ruled out. Also, switching GARCH models that could well reduce the high levels of volatility persistence found by the GARCH type models that I have examined. The MDH rationalisation of GARCH type models was extended to the examination of CGARCH models, thereby adding to the existing literature on the volatility-volume relationship. As the MDH only explained some of the GARCH effects, the identification and examination of other variables besides volume provides an avenue for further investigation. In terms of forecasting the thesis was of interest because there have been few comparative studies for individual stocks. Further extensions of the forecasting analysis can be provided by examining data of higher frequency than the daily level. This would reduce the impact of the inherent noise in the return generating process but can introduce problems due to market microstructure effects, for example, intraday periodic volatility patterns and bid-ask spreads.

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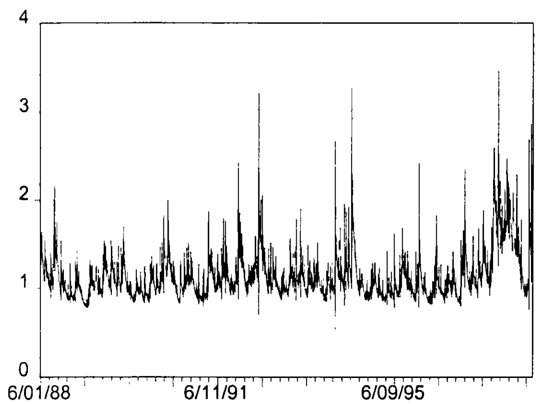
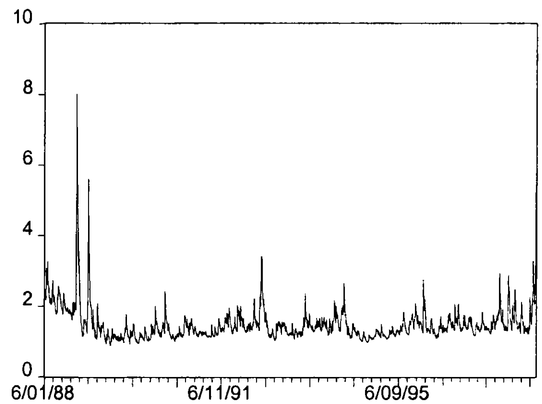
Appendix 1

Figure 3.1



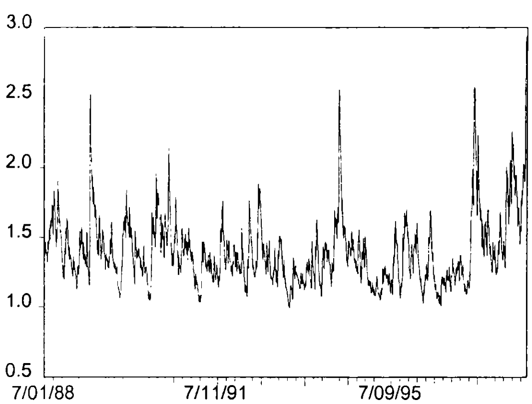
Reckitt & Colman
GARCH model conditional standard deviation

Figure 3.2



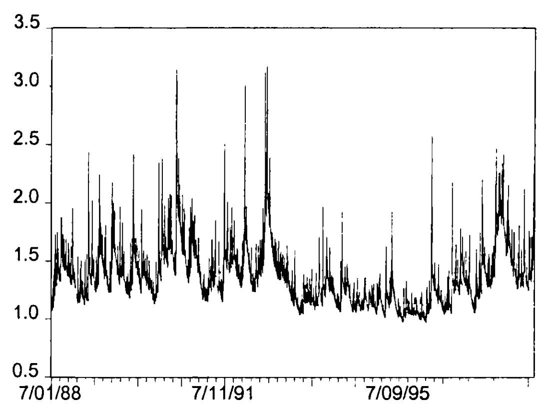
Enterprise Oil
Component model conditional standard deviation

Figure 3.3



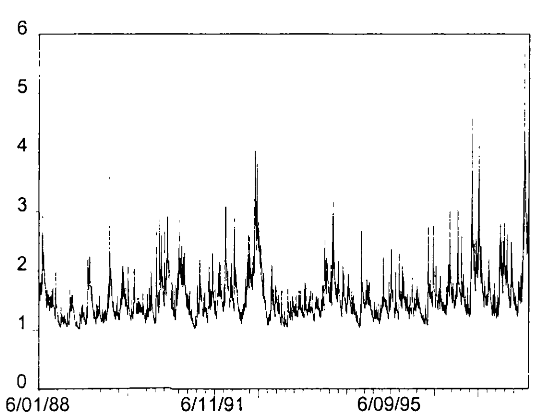
General Electric
Component model conditional standard deviation

Figure 3.4



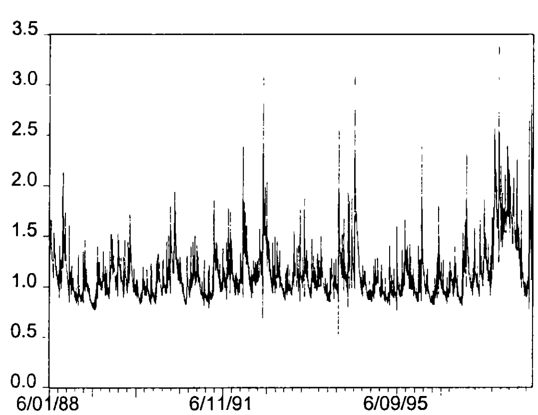
Marks & Spencer
Component model conditional standard deviation

Figure 3.5



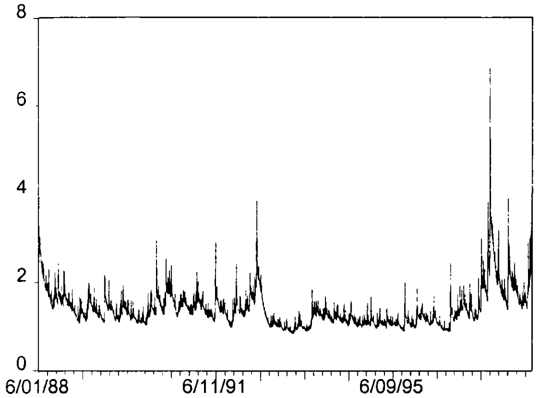
Rank Group
Component model conditional standard deviation

Figure 3.6



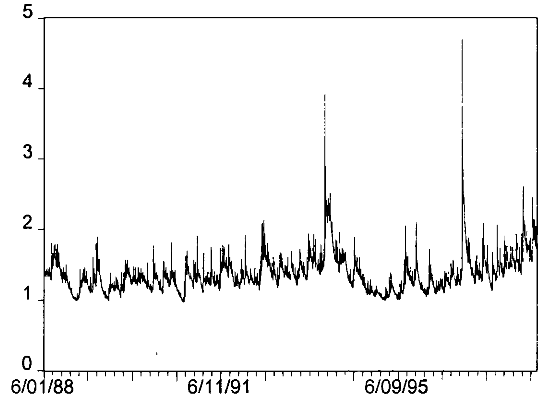
Reckitt & Colman
Component model conditional standard deviation

Figure 3.7



Reed International
Component model conditional standard deviation

Figure 3.8



Sainsbury
Component model conditional standard deviation

Table 3.1. Statistics for the Stock Returns and the FTSE 100 Returns

Stock/Index	Mean	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	JB
FTSE 100	0.0402	5.4396	-4.1399	0.8231	0.0151	5.0911	508*
Asda	0.0105	17.383	-33.851	2.2757	-1.2618	27.008	67,626*
Associated British Foods	0.0456	8.6013	-7.4395	1.1804	-0.1139	9.1541	4,401*
BAA	0.0585	8.4208	-6.7502	1.2541	0.1163	5.5434	757*
BAT Industries	0.0395	25.992	-9.2593	1.5707	1.5655	31.266	93,854*
BOC	0.0248	6.2351	-9.2373	1.2667	-0.1592	6.2333	1,225*
BG	0.0401	8.9218	-12.609	1.4884	-0.2068	7.1125	1,982*
BP	0.0407	7.3902	-15.072	1.3610	-0.2638	9.9563	5,648*
BT	0.0453	7.6373	-9.5897	1.3129	0.2678	6.7479	1,663*
Barclays	0.0551	14.379	-10.790	1.6174	0.1495	8.2558	3,216*
Bass	0.0272	10.103	-9.8498	1.3024	0.0803	7.9003	2,790*
Blue Circle	0.0099	15.635	-18.487	1.8143	0.0474	11.881	9,153*
Boots	0.0510	7.6577	-8.5861	1.3762	0.0003	5.5306	743*
British Airways	0.0403	9.7323	-9.0117	1.6781	-0.0447	5.8477	942*
CGU	0.0360	8.2888	-7.5544	1.4977	0.0842	5.5042	731*
Cable & Wireless	0.0463	13.954	-18.047	1.6787	-0.2994	11.476	8,378*
Cadbury Schweppes	0.0461	10.606	-7.1108	1.4261	0.7663	8.1157	3,309*
Diageo	0.0514	15.402	-9.2238	1.4109	0.7112	11.843	9,309*
EMI	0.0278	17.887	-10.739	1.3487	0.5120	17.712	25,279*
Enterprise Oil	0.0135	25.565	-17.139	1.6451	1.1812	32.068	98,698*
General Electric	0.0380	10.004	-8.5190	1.4343	0.1801	5.9663	1,036*
Glaxo Wellcome	0.0716	18.809	-13.895	1.6315	0.4351	11.880	9,238*
GRE	0.0165	15.105	-8.0039	2.0221	0.3565	5.4824	774*
ICI	0.0047	8.2271	-15.525	1.3639	-0.3614	11.864	9,178*
Ladbroke	0.0135	15.320	-15.415	1.9173	0.0988	8.9827	4,158*
Land Securities	0.0234	5.9037	-4.9462	1.1139	0.1723	4.9541	457*
Legal & General	0.0639	11.811	-9.3414	1.6231	0.1716	6.6396	1,551*
Marks & Spencer	0.0377	8.0689	-7.2245	1.3978	0.1939	5.4718	726*
Natwest Bank	0.0427	15.415	-8.1678	1.7041	0.4222	7.6965	2,642*
Pearson	0.0389	10.115	-9.4174	1.4782	0.2601	7.3809	2,259*

Table 3.1 (continued). Statistics for the Stock Returns and the FTSE 100 Returns

Stock/Index	Mean	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	JB
Prudential	0.0587	9.5725	-6.8670	1.5780	0.1808	4.8709	421*
RMC	0.0226	19.237	-13.353	1.5372	0.3175	16.936	22,585*
Rank Group	0.0087	12.972	-10.002	1.5783	0.0235	7.9670	2,863*
Reckitt & Colman	0.0390	7.8011	-7.4620	1.1743	0.1277	7.1574	2,013*
Reed International	0.0337	16.749	-8.8253	1.4523	0.4033	12.238	9,979*
Reuters	0.0508	7.4122	-16.218	1.7059	-0.6940	9.0790	4,512*
Rio Tinto	0.0208	8.8805	-7.7962	1.4610	-0.1637	5.7882	915*
Rolls Royce	0.0160	9.2032	-10.215	1.9032	-0.0559	5.2776	603*
Royal & Sun Alliance Ins.	0.0317	18.533	-8.0888	1.7475	0.9022	11.510	8,782*
Royal Bank of Scotland	0.0643	9.9091	-12.862	1.7109	0.1016	7.1135	1,968*
Safeway	0.0208	7.4564	-17.726	1.5590	-0.5572	10.654	6,942*
Sainsbury	0.0320	6.9270	-13.938	1.3829	-0.4372	9.1379	4,461*
Scottish & Newcastle	0.0486	14.311	-23.944	1.4496	-1.0859	34.907	118,682*
Standard chartered	0.0517	14.651	-15.151	1.9778	-0.0287	7.8128	2,688*
Tesco	0.0420	8.2019	-6.6903	1.5219	0.0754	4.1360	152*
Unilever	0.0563	5.4809	-5.4222	1.1161	0.1845	5.0460	502*

Notes: The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, $JB \sim \chi_2^2$. An asterisk denotes significance in the JB statistic at the 5% level.

Table 3.2. GARCH/GJR Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero.

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1
FTSE 100	0.0346* (0.0144)	0.0734* (0.0197)	0.0118* (0.0038)	0.0255* (0.0091)	_	0.9359* (0.0109)	_	0.0435* (0.0109)
Asda	0.0658* (0.0322)	0.0144 (0.0226)	0.0666* (0.0231)	0.0983* (0.0443)	_	0.8985* (0.0326)	_	_
Associated British Foods	0.0421* (0.0181)	0.1270* (0.0228)	0.0039 (0.0026)	0.1333* (0.0295)	-0.1330* (0.0289)	0.9813* (0.0059)	_	0.0327* (0.0097)
BAA	0.0512* (0.0215)	0.0994* (0.0212)	0.0109* (0.0054)	0.1989* (0.0382)	-0.1805* (0.0377)	0.9749* (0.0090)	_	_
BAT Industries	0.0330 (0.0269)	0.0515* (0.0232)	0.0788* (0.0272)	0.0501* (0.0109)	_	0.9151* (0.0199)	_	_
BOC	0.0294 (0.0230)	0.0702* (0.0215)	0.0152 (0.0080)	0.0295* (0.0068)	_	0.9608* (0.0090)	_	_
BG	0.0238 (0.0256)	0.0721* (0.0219)	0.0779* (0.0261)	0.0686* (0.0193)	_	0.8972* (0.0260)	_	_
BT	0.0308 (0.0224)	0.1094* (0.0213)	0.0205 (0.0125)	0.1382* (0.0351)	-0.1051* (0.0344)	0.9555* (0.0150)	_	_
Barclays	0.0496 (0.0258)	0.1180* (0.0211)	0.0548* (0.0175)	0.0755* (0.0145)	_	0.9056* (0.0184)	_	_
Bass	0.0166 (0.0213)	0.1203* (0.0220)	0.0024 (0.0034)	0.1740* (0.0455)	-0.1608* (0.0445)	0.9860* (0.0063)	_	_
Blue Circle	0.0021 (0.0289)	0.1153* (0.0274)	0.0247* (0.0090)	0.1169* (0.0418)	-0.1045* (0.0417)	0.9636* (0.0082)	_	0.0349* (0.0168)
Boots	0.0529* (0.0250)	0.0767* (0.0203)	0.0295* (0.0104)	0.0380* (0.0087)	_	0.9464* (0.0118)	_	_
British Airways	0.0467 (0.0283)	0.0949* (0.0222)	0.0177* (0.0079)	0.1157* (0.0316)	-0.1068* (0.0306)	0.9733* (0.0072)	_	0.0231* (0.0101)
CGU	0.0300 (0.0256)	0.0812* (0.0212)	0.0357* (0.0149)	0.1232* (0.0281)	-0.0743* (0.0306)	0.9355* (0.0153)	_	_
Cadbury Schweppes	0.0278 (0.0239)	0.0932* (0.0212)	0.1021* (0.0334)	0.0784* (0.0168)	_	0.8699* (0.0286)	_	_

Table 3.2 (continued). GARCH/GJR Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1
Diageo	0.0517* (0.0247)	0.0844* (0.0213)	0.0280* (0.0111)	0.0179* (0.0064)	_	0.9500* (0.0114)	_	0.0429* (0.0139)
EMI	0.0259 (0.0219)	0.1101* (0.0206)	0.0066 (0.0070)	0.0610* (0.0255)	-0.0589* (0.0253)	0.9811* (0.0063)	_	0.0274* (0.0087)
Enterprise Oil	0.0171 (0.0339)	0.1016* (0.0310)	0.0480* (0.0186)	0.0934* (0.0272)	_	0.9003* (0.0165)	_	_
General Electric	0.0299 (0.0257)	0.0854* (0.0197)	0.0594* (0.0242)	0.0548* (0.0131)	_	0.9173* (0.0207)	_	_
Glaxo Wellcome	0.0788* (0.0282)	0.0705* (0.0217)	0.0466* (0.0167)	0.0560* (0.0148)	_	0.9283* (0.0133)	_	_
ICI	0.0226 (0.0240)	0.1190* (0.0218)	0.0235* (0.0111)	0.0426* (0.0106)	_	0.9464* (0.0116)	_	_
Ladbroke	-0.0082 (0.0319)	0.0534* (0.0253)	0.0301* (0.0124)	0.1419* (0.0440)	-0.1375* (0.0433)	0.9606* (0.0112)	_	0.0585* (0.0255)
Land Securities	0.0209 (0.0193)	0.0748* (0.0207)	0.0348* (0.0114)	0.0598* (0.0126)	_	0.9133* (0.0194)	_	_
Legal & General	0.0517* (0.0260)	0.1026* (0.0220)	0.0145* (0.0064)	0.1154* (0.0361)	-0.0895* (0.0352)	0.9684* (0.0070)	_	_
Marks & Spencer	0.0163 (0.0245)	0.0868* (0.0213)	0.0327* (0.0139)	0.1319* (0.0351)	-0.0986* (0.0344)	0.9501* (0.0134)	_	_
Natwest Bank	0.0357 (0.0273)	0.0659* (0.0195)	0.0713* (0.0137)	0.0912* (0.0074)	_	0.8878* (0.0104)	_	_
Pearson	0.0393 (0.0252)	0.0707* (0.0214)	0.1007* (0.0285)	0.0706* (0.0157)	_	0.8812* (0.0241)	_	_
Prudential	0.0547 (0.0285)	0.0774* (0.0211)	0.1926* (0.0693)	0.0812* (0.0189)	_	0.8416* (0.0395)	_	_
RMC	0.0248 (0.0232)	0.1253* (0.0267)	0.0103* (0.0057)	0.1393* (0.0492)	-0.1076* (0.0501)	0.9646* (0.0075)	_	_
Rank Group	0.0141 (0.0277)	0.0693* (0.0222)	0.1187* (0.0365)	0.0930* (0.0193)	_	0.8623* (0.0248)	_	_
Reckitt & Colman	0.0273 (0.0198)	0.1399* (0.0221)	0.0700* (0.0294)	0.1628* (0.0295)	-0.0813* (0.0317)	0.3822* (0.1589)	0.4858* (0.1321)	_
Reed International	0.0216 (0.0243)	0.1042* (0.0218)	0.0138* (0.0059)	0.1457* (0.0375)	-0.1347* (0.0357)	0.9669* (0.0072)	_	0.0317* (0.0156)
Reuters	0.0568* (0.0272)	0.1654* (0.0248)	0.0353* (0.0101)	0.1832* (0.0687)	-0.1777* (0.0670)	0.9623* (0.0089)	_	0.0368* (0.0125)

Table 3.2 (continued). GARCH/GJR Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1
Rio Tinto	0.0145 (0.0239)	0.1011* (0.0211)	0.0187* (0.0068)	0.0779* (0.0333)	-0.0669* (0.0337)	0.9576* (0.0095)	–	0.0429* (0.0136)
Royal & Sun Alliance Ins.	0.0658* (0.0318)	0.0961* (0.0214)	0.0059 (0.0053)	0.0253* (0.0098)	–	0.9744* (0.0107)	–	–
Royal Bank of Scotland	0.0477 (0.0285)	0.1106* (0.0224)	0.0149 (0.0098)	0.1344* (0.0314)	-0.1100* (0.0299)	0.9712* (0.0088)	–	–
Sainsbury	0.0355 (0.0252)	0.1273* (0.0211)	0.0520* (0.0187)	0.0493* (0.0137)	–	0.9253* (0.0180)	–	–
Scottish & Newcastle	0.0732* (0.0340)	0.0667* (0.0242)	0.0959* (0.0285)	0.1517* (0.0416)	–	0.8310* (0.0292)	–	–
Standard Chartered	-0.0914* (0.0306)	0.1084* (0.0216)	0.0362* (0.0148)	0.0591* (0.0108)	–	0.9332* (0.0116)	–	–
Unilever	0.0500* (0.0199)	0.1448* (0.0206)	0.0095* (0.0041)	0.0331* (0.0068)	–	0.9593* (0.0078)	–	–

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level. The mean equations for BAT Industries and RMC include a dummy variable term to remove the effect of one-off large outliers (BAT Industries 25.9 per cent return on 11/7/1989 and RMC 19.2 per cent return on 1/6/1998).

Table 3.3. GARCH/GJR Model Volatility Persistence Statistics

Stock/Index	Volatility Persistence	Half-life (days)	Wald ($\lambda = 1$)	Stock/Index	Volatility Persistence	Half-life (days)	Wald ($\lambda = 1$)	Stock/Index	Volatility Persistence	Half-life (days)	Wald ($\lambda = 1$)
FTSE 100	0.9832	40.91	7.0432*	Cadbury Schweppes	0.9483	13.06	8.0619*	RMC	0.9964	191.40	0.9806
Asda	0.9969	219.91	0.0472	Diageo	0.9893	64.55	2.2418	Rank Group	0.9553	15.14	8.0474*
Associated British Foods	0.9981	364.47	0.3600	EMI	0.9969	223.25	0.3802	Reckitt & Colman	0.9495	13.38	5.2530*
BAA	0.9934	104.44	3.3551	Enterprise Oil	0.9937	106.68	0.0971	Reed International	0.9938	111.45	2.5503
BAT Industries	0.9652	19.57	8.3029*	General Electric	0.9721	24.50	4.9581*	Reuters	0.9863	50.22	12.315*
BOC	0.9903	71.11	3.4007	Glaxo Wellcome	0.9836	41.92	3.2989	Rio Tinto	0.9902	70.05	5.8783*
BG	0.9658	19.92	7.8472*	ICI	0.9890	62.88	1.8087	Royal & Sun Alliance Ins.	0.9997	2,003	0.0206
BT	0.9886	60.46	2.0639	Ladbroke	0.9942	118.76	2.5826	Royal Bank of Scotland	0.9956	157.19	1.1826
Barclays	0.9811	36.34	4.1311*	Land Securities	0.9731	25.42	7.4001*	Sainsbury	0.9746	26.89	8.0018*
Bass	0.9992	866.09	0.1141	Legal & General	0.9943	121.26	3.1336	Scottish & Newcastle	0.9827	39.72	0.4653
Blue Circle	0.9933	103.71	2.4897	Marks & Spencer	0.9865	60.00	4.6011*	Standard Chartered	0.9923	90.01	1.9560
Boots	0.9898	67.61	4.8282*	Natwest Bank	0.9794	33.30	11.501*	Unilever	0.9924	90.78	3.9931*
British Airways	0.9937	110.30	1.7915	Pearson	0.9518	14.03	10.568*				
CGU	0.9844	44.02	4.3953*	Prudential	0.9228	8.62	8.1702*				

Notes: Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom. An asterisk denotes significance at the 5% level.

Table 3.4. GARCH/GJR Model Residual Diagnostics

Stock/Index	Mean	Standard Deviation	Skewness	Kurtosis	JB	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
FTSE 100	0.0018	0.8194	0.0080	4.9706	450*	0.0629	0.8845	4.3734	0.3281	3.0668	4.9078	0.3278	0.6185	0.4977
Asda	-0.0537	2.2773	-1.2393	26.773	66,297*	2.2413	4.0392	11.433	1.1984	1.8243	3.1119	1.1963	0.3697	0.3049
Associated British Foods	-0.0026	1.1799	-0.0982	9.4821	4,879*	0.0594	9.3556	16.632	0.3760	4.7684	9.0617	0.3753	0.8982	0.8149
BAA	0.0019	1.2514	0.0955	5.4395	695*	0.4172	4.7872	7.0104	0.0342	6.6004	8.8490	0.0342	1.3677	0.9517
BAT Industries	-0.0047	1.4897	-0.0404	5.4844	717*	0.4197	10.840	19.680*	0.0831	2.1927	10.609	0.0829	0.4410	1.0476
BOC	-0.0080	1.2614	-0.1936	6.2814	1,266*	0.2866	5.5811	10.122	0.2901	1.3013	5.0338	0.2895	0.2573	0.5133
BG	0.0199	1.4855	-0.2057	7.2699	2,135*	0.3041	3.0343	10.271	2.6718	5.6307	9.4908	0.0024	1.1490	0.9553
BT	0.0106	1.3071	0.2237	6.7086	1,619*	0.1561	4.2027	10.198	0.0008	1.1337	10.563	0.0008	0.2247	1.0732
Barclays	-0.0009	1.6084	0.1864	8.7534	3,857*	0.0611	2.6710	10.282	0.0911	1.1037	4.2556	0.0909	0.2214	0.4212
Bass	0.0071	1.2906	0.0847	7.6267	2,487*	1.7532	10.078	20.243*	0.0017	0.8061	8.4561	0.0017	0.1617	0.8119
Blue Circle	0.0073	1.8102	0.0772	11.856	9,103*	0.0013	5.7340	13.994	0.0190	4.1599	5.9173	0.0190	0.8349	0.6937
Boots	-0.0076	1.3710	-0.0152	5.5379	747*	0.0662	1.9289	24.348*	0.8702	7.5382	10.911	0.8687	1.5087	1.0999
British Airways	-0.0108	1.6720	-0.0207	5.7672	889*	0.1178	2.6792	10.348	0.6302	7.4663	9.6507	0.6290	1.5412	0.9846
CGU	0.0023	1.4927	0.0899	5.4645	708*	0.4084	7.4484	17.937	0.0254	2.1532	5.2571	0.0254	0.4355	0.5192
Cadbury Schweppes	0.0141	1.4210	0.6950	7.8131	2,912*	0.0115	6.6532	16.837	1.1367	5.4852	7.9316	1.1372	1.0696	0.7640
Diageo	-0.0037	1.4090	0.7364	11.893	9,428*	0.0113	6.7520	19.302*	0.8284	1.5541	1.7584	0.8270	0.3060	0.1744
EMI	-0.0017	1.3421	0.5109	17.462	24,384*	0.0121	4.9246	11.142	0.0057	0.1600	6.5783	0.0180	0.0319	0.6554
Enterprise Oil	-0.0050	1.6343	1.1090	32.695	102,894*	3.1407	6.6059	14.069	0.0048	0.7598	1.3049	0.0048	0.1504	0.1279

Table 3.4 (continued). GARCH/GJR Model Residual Diagnostics

Stock/Index	Mean	Standard Deviation	Skewness	Kurtosis	JB	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
General Electric	0.0052	1.4283	0.1760	5.8821	978*	0.1779	4.9719	19.464*	0.4427	4.2193	7.7402	0.4482	0.9279	0.8770
Glaxo Wellcome	-0.0130	1.6292	0.4398	11.930	9,341*	0.5483	8.4571	16.446	0.2219	1.8188	5.2086	0.2214	0.3594	0.5083
ICI	-0.0193	1.3512	-0.3593	11.573	8,586*	0.1237	5.1847	6.6480	1.8466	2.4052	5.8190	1.8448	0.4763	0.6025
Ladbroke	0.0203	1.9139	0.0998	8.9869	4,162*	0.0629	7.2937	10.588	0.3857	4.3443	6.6223	0.3850	0.8483	0.6549
Land Securities	-0.0005	1.1127	0.1405	4.9406	446*	0.0038	2.9542	9.6520	1.6936	1.8988	4.6494	1.6911	0.3867	0.4630
Legal & General	0.0068	1.6226	0.1622	6.5304	1,459*	0.1985	2.9552	15.229	0.0033	2.7032	5.9841	0.0033	0.5376	0.5722
Marks & Spencer	0.0193	1.3933	0.1495	5.3960	676*	0.0345	8.2513	21.281*	0.1387	2.1138	3.6570	0.1384	0.4205	0.3705
Natwest Bank	0.0035	1.7018	0.4382	8.0201	3,012*	0.2128	8.3329	22.436*	1.2307	4.9228	8.5386	1.2287	1.0189	0.8696
Pearson	-0.0035	1.4777	0.2578	7.3596	2,235*	0.1149	7.3938	10.722	0.3765	1.1360	4.5405	0.3760	0.2265	0.4591
Prudential	-0.0015	1.5728	0.1574	4.8266	399*	0.2678	14.964*	27.022*	0.7748	2.3046	4.8877	0.7734	0.4472	0.4683
RMC	-0.0105	1.5003	-0.5285	11.162	7,857*	0.0009	6.0603	10.570	1.6213	2.7108	5.5759	1.6190	0.5279	0.5312
Rank Group	-0.0076	1.5733	0.0093	7.9061	2,792*	0.1320	3.6185	11.742	0.7918	7.4849	9.4080	0.7906	1.4451	0.9064
Reckitt & Colman	-0.0051	1.1663	0.0960	7.3959	2,246*	0.0010	5.9294	11.022	0.4587	0.7383	5.4587	0.4578	0.1486	0.5469
Reed International	0.0065	1.4424	0.3930	12.279	10,060*	0.3170	3.4278	3.6127	0.4061	1.0882	3.3998	0.4054	0.2138	0.3417
Reuters	-0.0158	1.6904	-0.5881	8.7898	4,049*	0.5488	12.767*	14.953	0.0172	2.0874	3.3470	0.0038	0.4180	0.3597
Rio Tinto	0.0041	1.4565	-0.1267	5.7691	897*	0.2930	8.1417	10.373	0.2026	3.8599	11.779	0.2022	0.7815	1.2499
Royal & Sun Alliance Ins.	-0.0370	1.7421	0.9231	11.588	8,951*	0.9485	5.1073	13.254	0.0186	0.2769	1.7272	0.0186	0.0555	0.1709
Royal Bank of Scotland	0.0109	1.7053	0.0761	7.1434	1,995*	0.0879	6.8840	13.265	0.0345	2.2817	3.4062	0.0345	0.4512	0.3241

Table 3.4 (continued). GARCH/GJR Model Residual Diagnostics

Stock/Index	Mean	Standard Deviation	Skewness	Kurtosis	JB	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Sainsbury	-0.0057	1.3743	-0.4203	9.4233	4,868*	0.0942	2.8709	9.3726	0.0647	1.7882	3.9769	0.0646	0.3567	0.3877
Scottish & Newcastle	-0.0284	1.4481	-1.0998	35.331	121,813*	0.1739	5.3085	7.7941	0.0371	0.2444	0.5535	0.0370	0.0490	0.0561
Standard Chartered	0.0478	1.9603	-0.0457	7.6443	2,503*	0.8161	3.8333	18.191	1.8554	6.1402	9.9556	1.8533	1.1955	0.9752
Unilever	-0.0022	1.1071	0.1595	5.0743	511*	0.0005	2.3922	6.8166	1.2112	5.9363	8.8302	1.2096	1.1326	0.8047

Notes: The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, $JB \sim \chi_2^2$. An asterisk denotes significance in the JB statistic at the 5% level. Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 3.5. CGARCH/ACGARCH Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β
Asda	0.0806* (0.0341)	_	6.0529 (5.6873)	0.9947* (0.0053)	0.0376* (0.0156)	0.1894 (0.1169)	_	0.3481* (0.1742)
Associated British Foods	0.0545* (0.0187)	0.1358* (0.0228)	1.4470* (0.6195)	0.9962* (0.0045)	0.0227* (0.0075)	0.1297* (0.0298)	_	0.2140 (0.1944)
BAA	0.0516* (0.0214)	0.1032* (0.0215)	1.6575* (0.2625)	0.9927* (0.0046)	0.0189* (0.0090)	0.1817* (0.0373)	_	0.2701* (0.1229)
BG	0.0168 (0.0254)	0.0720* (0.0220)	2.3328* (0.4540)	0.9857* (0.0069)	0.0409* (0.0131)	0.0853* (0.0363)	_	0.4097 (0.3113)
BT	0.0301 (0.0223)	0.1095* (0.0213)	1.7855* (0.3186)	0.9870* (0.0090)	0.0350* (0.0111)	0.1020* (0.0335)	_	0.0502 (0.2211)
Barclays	0.0427 (0.0257)	0.1092* (0.0000)	2.8902* (0.8951)	0.9937* (0.0047)	0.0303* (0.0111)	0.0437 (0.0307)	0.1106* (0.0508)	0.7204* (0.0737)
Bass	0.0173 (0.0214)	0.1257* (0.0220)	1.9169* (0.9565)	0.9977* (0.0036)	0.0144* (0.0060)	0.1443* (0.0448)	_	0.1422 (0.1891)
Blue Circle	0.0103 (0.0286)	0.1154* (0.0251)	3.3738* (1.0466)	0.9900* (0.0054)	0.0379* (0.0129)	0.0857* (0.0378)	_	0.5757* (0.1746)
Boots	0.0603* (0.0243)	0.0806* (0.0198)	1.8378* (0.2903)	0.9909* (0.0040)	0.0235* (0.0067)	0.0911* (0.0381)	-0.0966* (0.0436)	0.7177* (0.1316)
British Airways	0.0521 (0.0277)	0.0894* (0.0208)	2.6601* (0.5576)	0.9951* (0.0032)	0.0192* (0.0066)	0.0030 (0.0224)	0.1680* (0.0472)	0.5701* (0.1187)
CGU	0.0426 (0.0252)	0.0860* (0.0213)	2.2647* (0.4516)	0.9935* (0.0047)	0.0232* (0.0091)	0.0379 (0.0270)	0.0701* (0.0353)	0.7665* (0.0787)
Cadbury Schweppes	0.0354* (0.0000)	0.0906* (0.0211)	1.9017* (0.2034)	0.9657* (0.0122)	0.0472* (0.0139)	0.1234* (0.0373)	-0.1461* (0.0487)	0.5586* (0.1783)
Diageo	0.0616* (0.0240)	0.1014* (0.0231)	2.3777* (0.8540)	0.9934* (0.0063)	0.0243* (0.0115)	0.0795* (0.0258)	_	0.6586* (0.1487)
EMI	0.0406 (0.0217)	0.1146* (0.0212)	2.0346 (1.5796)	0.9964* (0.0091)	0.0186* (0.0083)	0.0339* (0.0172)	_	0.8634* (0.1299)
Enterprise Oil	-0.0034 (0.0287)	0.0974* (0.0304)	2.0261* (0.4377)	0.9959* (0.0085)	-0.0080* (0.0022)	0.1014* (0.0370)	_	0.8279* (0.0498)
General Electric	0.0219* (0.0000)	0.0924* (0.0193)	2.1330* (0.2630)	0.9718* (0.0123)	0.0546* (0.0130)	-0.0511* (0.0245)	0.1031* (0.0400)	-0.6884* (0.2005)

Table 3.5 (continued). CGARCH/ACGARCH Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β
Glaxo Wellcome	0.0764* (0.0280)	0.0738* (0.0212)	3.0051* (1.3130)	0.9962* (0.0050)	0.0181 (0.0162)	0.0389* (0.0197)	_	0.8986* (0.0762)
ICI	0.0184 (0.0240)	0.1176* (0.0217)	2.0803* (0.7858)	0.9908* (0.0083)	0.0332* (0.0107)	0.0868* (0.0370)	_	0.3155 (0.2395)
Ladbroke	0.0245 (0.0317)	0.0536* (0.0253)	4.3237* (1.8332)	0.9922* (0.0047)	0.0442* (0.0161)	0.0960* (0.0403)	_	0.6631* (0.2078)
Land Securities	0.0190 (0.0192)	0.0774* (0.0206)	1.2380* (0.2406)	0.9952* (0.0034)	0.0155 (0.0095)	0.0565* (0.0174)	_	0.8450* (0.0605)
Legal & General	0.0552* (0.0259)	0.1023* (0.0220)	2.4907* (0.6021)	0.9937* (0.0036)	0.0260* (0.0081)	0.0751* (0.0312)	_	0.5497* (0.2260)
Marks & Spencer	0.0158 (0.0245)	0.0878* (0.0213)	1.9506* (0.2243)	0.9828* (0.0074)	0.0329* (0.0087)	0.0984* (0.0337)	_	-0.0578 (0.2282)
Pearson	0.0379 (0.0246)	0.0711* (0.0213)	2.0860* (0.3273)	0.9880* (0.0054)	0.0251* (0.0096)	0.0651* (0.0203)	_	0.7643* (0.1175)
Prudential	0.0539 (0.0281)	0.0761* (0.0210)	2.5332* (0.3051)	0.9909* (0.0062)	0.0173* (0.0080)	0.0906* (0.0312)	_	0.6232* (0.1196)
RMC	0.0259 (0.0232)	0.1451* (0.0231)	2.9000 (3.8584)	0.9978* (0.0060)	0.0232* (0.0062)	0.0693* (0.0330)	_	0.5010* (0.2111)
Rank Group	0.0110 (0.0278)	0.0769* (0.0228)	2.6573* (0.4262)	0.9622* (0.0155)	0.0784* (0.0256)	0.0976* (0.0407)	_	-0.0638 (0.3046)
Reckitt & Colman	0.0276 (0.0198)	0.1395* (0.0221)	1.3686* (0.1710)	0.9639* (0.0141)	0.0534* (0.0128)	0.1032* (0.0224)	_	-0.5497* (0.1457)
Reed International	0.0301 (0.0240)	0.1069* (0.0217)	2.1671* (0.7006)	0.9897* (0.0068)	0.0416* (0.0120)	0.1154* (0.0330)	_	-0.0588 (0.1918)
Reuters	0.0751* (0.0272)	0.1658* (0.0249)	2.7165* (0.5758)	0.9879* (0.0051)	0.0306* (0.0119)	0.1764* (0.0696)	_	0.2372 (0.1382)
Rio Tinto	0.0358 (0.0234)	0.1045* (0.0209)	1.8625* (0.3285)	0.9926* (0.0058)	0.0252* (0.0125)	0.0687* (0.0267)	_	0.7633* (0.1180)
Royal Bank of Scotland	0.0471 (0.0285)	0.1118* (0.0221)	3.2455* (0.9828)	0.9946* (0.0047)	0.0245* (0.0071)	0.0997* (0.0284)	_	0.4283* (0.1771)
Sainsbury	0.0324 (0.0260)	0.1278* (0.0205)	2.0438* (0.3806)	0.9813* (0.0077)	0.0384* (0.0128)	0.0644* (0.0271)	_	-0.3564 (0.3306)
Standard Chartered	-0.0784* (0.0301)	0.1039* (0.0226)	4.2798* (1.7986)	0.9940* (0.0044)	0.0423* (0.0122)	0.1002* (0.0255)	_	0.6125* (0.1210)
Unilever	0.0462* (0.0193)	0.1406* (0.0205)	1.1647* (0.2106)	0.9935* (0.0040)	0.0241* (0.0062)	0.0664* (0.0270)	_	0.5244* (0.2199)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 3.6. CGARCH/ACGARCH Model Volatility Persistence Statistics

Stock/Index	Permanent Component			Transitory Component			
	Volatility Persistence	Half-life (days)	Wald ($\lambda = 1$)	Volatility Persistence	Half-life (days)	Wald ($\alpha = \beta = 0$)	Wald ($\alpha + \delta_s = 0$)
Asda	0.9947	133.51	1.0023	0.5375	1.16	23.947*	–
Associated British Foods	0.9962	184.00	0.7081	0.3437	0.65	28.185*	–
BAA	0.9927	94.35	2.5656	0.4518	0.87	50.290*	–
BG	0.9857	48.21	4.2410*	0.4950	0.99	8.9330*	–
BT	0.9870	52.93	2.0875	0.1522	0.37	9.4002*	–
Barclays	0.9937	109.07	1.8368	0.8194	3.48	–	15.736*
Bass	0.9977	301.55	0.4172	0.2865	0.55	15.452*	–
Blue Circle	0.9900	69.26	3.4315	0.6614	1.68	13.687*	–
Boots	0.9909	75.54	5.2410*	0.7605	2.53	–	0.0784
British Airways	0.9951	141.11	2.3167	0.6570	1.65	–	15.822*
CGU	0.9935	106.74	1.8890	0.8365	3.88	–	13.998*
Cadbury Schweppes	0.9657	19.86	7.9641*	0.6089	1.40	–	0.5276
Diageo	0.9934	104.11	1.1332	0.7381	2.28	66.882*	–
EMI	0.9964	194.74	0.1515	0.8974	6.40	83.286*	–
Enterprise Oil	0.9959	169.25	0.2302	0.9294	9.46	610.42*	–
General Electric	0.9718	24.25	5.2216*	-0.6879	–	–	3.9027*
Glaxo Wellcome	0.9962	184.25	0.5664	0.9374	10.73	316.61*	–
ICI	0.9908	75.20	1.2229	0.4023	0.76	7.8202*	–
Ladbroke	0.9922	88.21	2.7664	0.7591	2.52	49.672*	–
Land Securities	0.9952	143.70	1.9544	0.9015	6.68	296.91*	–
Legal & General	0.9937	110.33	3.0783	0.6248	1.47	37.346*	–
Marks & Spencer	0.9828	40.03	5.4065*	0.0406	0.22	8.8249*	–
Pearson	0.9880	57.38	4.8579*	0.8294	3.71	97.566*	–
Prudential	0.9909	76.01	2.1496	0.7138	2.06	83.109*	–
RMC	0.9978	309.93	0.1374	0.5703	1.23	27.654*	–
Rank Group	0.9622	17.97	5.9830*	0.0338	0.20	6.4686*	–
Reckitt & Colman	0.9639	18.86	6.5573*	-0.4465	–	141.73*	–
Reed International	0.9897	66.91	2.2641	0.0566	0.24	13.732*	–
Reuters	0.9879	56.95	5.7124*	0.4136	0.79	21.375*	–

Table 3.6 (continued). CGARCH/ACGARCH Model Volatility Persistence Statistics							
Stock/Index	**Permanent Component**			**Transitory Component**			
	Volatility Persistence	**Half-life (days)**	**Wald ($\lambda = 1$)**	**Volatility Persistence**	**Half-life (days)**	**Wald ($\alpha = \beta = 0$)**	**Wald ($\alpha + \delta_s = 0$)**
Rio Tinto	0.9926	93.50	1.6042	0.8320	3.77	107.34*	–
Royal Bank of Scotland	0.9946	128.37	1.3027	0.5280	1.09	25.031*	–
Sainsbury	0.9813	36.76	5.8583*	-0.3564	–	11.814*	–
Standard Chartered	0.9940	115.04	1.8366	0.7127	2.05	68.760*	–
Unilever	0.9935	106.16	2.6127	0.5909	1.32	16.057*	–

Notes: Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom. An asterisk denotes significance at the 5% level.

Table 3.7. CGARCH/ACGARCH Model Residual Diagnostics

Stock/Index	Mean	Standard Deviation	Skewness	Kurtosis	JB	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Asda	-0.0701	2.2757	-1.2618	27.008	67,276*	2.8561	4.8623	14.055	0.0814	0.9933	1.7155	0.0812	0.1941	0.1596
Associated British Foods	-0.0155	1.1803	-0.0968	9.5055	4,915*	0.0109	9.7211	16.325	0.2293	2.3012	6.3867	0.2289	0.4471	0.5903
BAA	-0.0004	1.2484	0.0809	5.4219	684*	0.3155	4.2875	6.5954	0.0340	4.3409	6.6440	0.0340	0.8649	0.6814
BG	0.0196	1.4852	-0.2055	7.2767	2,142*	0.3387	2.9089	9.8401	0.0016	7.7102	10.750	0.0016	1.5241	1.0727
BT	0.0113	1.3071	0.2240	6.7077	1,619*	0.1562	4.2099	10.201	0.0054	1.1981	12.166	1.0524	0.2376	1.1074
Barclays	0.0047	1.6059	0.1789	8.7477	3,848*	0.8135	3.4819	11.224	0.0316	1.7348	6.9512	0.0315	0.3505	0.6833
Bass	0.0062	1.2905	0.0847	7.6119	2,471*	1.2086	9.1951	19.576*	0.0444	0.6688	8.1763	0.0447	0.1373	0.8120
Blue Circle	-0.0026	1.8081	0.0744	11.896	9,186*	0.0172	5.4722	14.155	0.0643	3.4624	6.0799	0.0641	0.6961	0.7240
Boots	-0.0151	1.3711	-0.0156	5.5375	747*	0.0566	2.1914	25.620*	0.1031	6.2148	9.3240	0.1029	1.1866	0.9262
British Airways	-0.0177	1.6695	-0.0275	5.7817	898*	0.4268	1.8884	10.851	0.0827	1.3212	2.9229	0.0825	0.2654	0.2962
CGU	-0.0104	1.4927	0.0901	5.4617	707*	0.2659	6.1078	16.507	1.8476	6.1296	8.0458	1.8449	1.2644	0.8248
Cadbury Schweppes	0.0067	1.4211	0.6974	7.8207	2,922*	0.1279	7.6532	18.817*	0.0576	3.2523	6.1985	0.0576	0.6570	0.6253
Diageo	-0.0157	1.4080	0.7373	11.928	9,499*	0.1816	6.5710	19.140*	0.0920	0.8383	1.1241	0.0919	0.1690	0.1119
EMI	-0.0166	1.3422	0.5102	17.438	24,302*	0.0160	4.3764	11.131	0.1042	1.2260	4.3694	0.1040	0.2429	0.4253
Enterprise Oil	0.0156	1.6345	1.1117	32.676	102,769*	2.7750	6.0098	16.415	0.0111	1.4947	2.0309	0.0111	0.2970	0.1990
General Electric	0.0129	1.4283	0.1756	5.8729	972*	0.0054	4.3724	19.069*	0.0865	4.7725	8.7746	0.0873	1.0201	0.9757
Glaxo Wellcome	-0.0108	1.6293	0.4399	11.929	9,337*	0.3532	7.9496	15.525	0.3297	2.0852	4.6464	0.3290	0.4134	0.4526
ICI	-0.0151	1.3512	-0.3594	11.579	8,597*	0.2949	5.8627	7.4829	0.1097	0.2818	4.4203	0.1096	0.0558	0.4393

Table 3.7 (continued). CGARCH/ACGARCH Model Residual Diagnostics

Stock/Index	Mean	Standard Deviation	Skewness	Kurtosis	JB	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Ladbroke	-0.0123	1.9139	0.0998	8.9869	4,162*	0.1363	6.8795	8.6399	0.0033	4.1373	6.4604	0.0033	0.8318	0.6491
Land Securities	0.0016	1.1123	0.1394	4.9463	448*	0.0169	2.8661	9.7234	0.3699	0.8449	3.8660	0.3692	0.1690	0.3823
Legal & General	0.0027	1.6224	0.1630	6.5350	1,462*	0.1857	2.7623	15.277	0.0984	2.5720	6.0498	0.0981	0.5154	0.6067
Marks & Spencer	0.0197	1.3933	0.1489	5.3951	676*	0.0191	8.2794	21.395*	0.1540	1.9557	3.4708	0.1537	0.3902	0.3520
Pearson	-0.0022	1.4778	0.2577	7.3594	2,235*	0.0125	7.4741	11.651	0.0031	0.9797	5.7066	0.0031	0.1944	0.5775
Prudential	-0.0007	1.5728	0.1578	4.8274	399*	0.3038	15.008*	28.319*	0.0027	0.7072	3.8810	0.0027	0.1403	0.3783
RMC	-0.0076	1.5409	0.1399	18.959	29,551*	1.1299	6.2814	9.7846	2.1224	2.3887	3.7224	2.1195	0.4781	0.3676
Rank Group	-0.0045	1.5734	0.0085	7.8943	2,779*	0.0129	4.0204	11.821	0.4015	7.6756	9.1337	0.4008	1.5106	0.8809
Reckitt & Colman	0.0049	1.1663	0.0961	7.3955	2,245*	0.0005	5.9137	11.039	0.3424	0.6266	5.3005	0.3418	0.1264	0.5309
Reed International	-0.0021	1.4425	0.3929	12.276	10,052*	0.2836	1.8710	3.2078	0.3297	0.5486	2.5905	0.3290	0.1046	0.2580
Reuters	-0.0341	1.6904	-0.5877	8.7888	4,047*	0.5332	11.879*	14.426	0.0011	1.1306	4.8270	0.0011	0.2267	0.4801
Rio Tinto	-0.0173	1.4566	-0.1254	5.7691	897*	0.2626	8.7175	11.796	0.7669	2.0648	9.4614	0.7657	0.4136	1.0199
Royal Bank of Scotland	0.0106	1.7053	0.0765	7.1475	1,998*	0.0578	6.4364	12.883	0.0019	0.7555	2.6977	0.0019	0.1494	0.2688
Sainsbury	-0.0047	1.3743	-0.4202	9.4238	4,869*	0.0746	2.7067	8.6499	0.1830	1.1287	3.7167	0.1826	0.2282	0.3641
Standard Chartered	0.0346	1.9603	-0.0444	7.6530	2,512*	1.1662	3.7680	18.421*	0.9690	1.8080	5.5726	0.9678	0.3585	0.5623
Unilever	0.0018	1.1071	0.1603	5.0740	511*	0.0506	2.4614	7.4286	0.4014	0.8773	3.0295	0.4007	0.1727	0.3148

Notes: The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, $JB \sim \chi_2^2$. An asterisk denotes significance in the JB statistic at the 5% level. Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 3.8. GARCH/GJR Model Conditional Mean and Variance Specifications (Monday Effect)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise and $M_t = 1$ when the day of the week is Monday and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero.

Stock/Index	μ	a_1	λ_d	Wald ($\lambda_d = 0$)	ω	α_1	α_2	β_1	γ_1
FTSE 100	0.0579* (0.0163)	0.0736* (0.0196)	-0.1176* (0.0364)	10.417*	0.0119* (0.0039)	0.0262* (0.0093)	–	0.9348* (0.0109)	0.0439* (0.0124)
Associated British Foods	0.0647* (0.0202)	0.1267* (0.0228)	-0.1128* (0.0473)	5.6870*	0.0038 (0.0025)	0.1360* (0.0298)	-0.1361* (0.0292)	0.9814* (0.0058)	0.0335* (0.0097)
BAA	0.0756* (0.0245)	0.0985* (0.0211)	-0.1263* (0.0548)	5.3031*	0.0110* (0.0054)	0.2009* (0.0388)	-0.1822* (0.0382)	0.9745* (0.0090)	–
BOC	0.0511* (0.0254)	0.0708* (0.0214)	-0.1101* (0.0506)	4.7405*	0.0156 (0.0082)	0.0303* (0.0070)	–	0.9598* (0.0094)	–
BG	0.0630* (0.0289)	0.0723* (0.0218)	-0.1952* (0.0647)	9.1022*	0.0732* (0.0246)	0.0674* (0.0189)	–	0.9005* (0.0251)	–
Barclays	0.0884* (0.0293)	0.1182* (0.0211)	-0.1963* (0.0640)	9.4244*	0.0550* (0.0175)	0.0767* (0.0147)	–	0.9044* (0.0186)	–
Blue Circle	0.0393 (0.0331)	0.1162* (0.0276)	-0.1836* (0.0708)	6.7258*	0.0242* (0.0090)	0.1194* (0.0432)	-0.1057* (0.0431)	0.9631* (0.0083)	0.0335* (0.0168)
British Airways	0.0940* (0.0313)	0.0941* (0.0223)	-0.2360* (0.0709)	11.073*	0.0174* (0.0075)	0.1151* (0.0313)	-0.1062* (0.0302)	0.9732* (0.0071)	0.0236* (0.0102)
CGU	0.0728* (0.0285)	0.0810* (0.0211)	-0.2160* (0.0618)	12.230*	0.0324* (0.0136)	0.1234* (0.0281)	-0.0762* (0.0305)	0.9387* (0.0143)	–
Cadbury Schweppes	0.0552* (0.0267)	0.0936* (0.0212)	-0.1374* (0.0588)	5.4553*	0.1037* (0.0341)	0.0792* (0.0169)	–	0.8682* (0.0291)	–
EMI	0.0634* (0.0248)	0.1115* (0.0207)	-0.1902* (0.0607)	9.8283*	0.0066 (0.0067)	0.0651* (0.0275)	-0.0628* (0.0273)	0.9808* (0.0061)	0.0276* (0.0087)
Enterprise Oil	0.0444 (0.0398)	0.1014* (0.0313)	-0.1379* (0.0696)	3.9270*	0.0483* (0.0183)	0.0936* (0.0279)	–	0.9000* (0.0166)	–
ICI	0.0472 (0.0261)	0.1186* (0.0218)	-0.1232* (0.0578)	4.5417*	0.0210* (0.0106)	0.0406* (0.0101)	–	0.9497* (0.0112)	–
Land Securities	0.0418* (0.0212)	0.0737* (0.0207)	-0.1036* (0.0492)	4.4414*	0.0348* (0.0115)	0.0598* (0.0126)	–	0.9133* (0.0194)	–

Table 3.8 (continued). GARCH/GJR Model Conditional Mean and Variance Specifications (Monday Effect)

Stock/Index	μ	a_1	λ_d	Wald ($\lambda_d = 0$)	ω	α_1	α_2	β_1	γ_1
Legal & General	0.0842* (0.0289)	0.1025* (0.0220)	-0.1602* (0.0664)	5.8235*	0.0142* (0.0063)	0.1168* (0.0358)	-0.0906* (0.0349)	0.9683* (0.0069)	–
Natwest Bank	0.0688* (0.0314)	0.0659* (0.0219)	-0.1703* (0.0682)	6.2282*	0.0705* (0.0185)	0.0914* (0.0180)	–	0.8879* (0.0185)	–
Prudential	0.0902* (0.0322)	0.0767* (0.0211)	-0.1791* (0.0673)	7.0760*	0.1935* (0.0689)	0.0820* (0.0190)	–	0.8403* (0.0396)	–
Rio Tinto	0.0393 (0.0269)	0.1027* (0.0211)	-0.1260* (0.0567)	4.9381*	0.0176* (0.0066)	0.0766* (0.0332)	-0.0672* (0.0335)	0.9595* (0.0093)	0.0435* (0.0131)
Royal & Sun Alliance Ins.	0.1061* (0.0341)	0.0954* (0.0214)	-0.2005* (0.0682)	8.6353*	0.0058 (0.0052)	0.0249* (0.0098)	–	0.9748* (0.0107)	–
Royal Bank of Scotland	0.0827* (0.0321)	0.1131* (0.0223)	-0.1765* (0.0782)	5.0906*	0.0155 (0.0102)	0.1281* (0.0313)	-0.1032* (0.0296)	0.9705* (0.0091)	–
Standard Chartered	-0.1479* (0.0346)	0.1095* (0.0215)	0.2861* (0.0724)	15.629*	0.0342* (0.0140)	0.0582* (0.0108)	–	0.9346* (0.0114)	–

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level. Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom.

Table 3.9. CGARCH/ACGARCH Model Conditional Mean and Variance Specifications (Monday Effect)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \varepsilon_t, \quad h_t = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\varepsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$

$$q_t = \omega + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - h_{t-1})$$

where $M_t = 1$ when the day of the week is Monday and zero otherwise, q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ε_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Stock/Index	μ	a_1	λ_d	Wald ($\lambda_d = 0$)	ω	ρ	φ	α	δ_s	β
Associated British Foods	0.0747* (0.0206)	0.1356* (0.0228)	-0.0986* (0.0486)	4.1115*	1.4496* (0.6387)	0.9964* (0.0044)	0.0225* (0.0073)	0.1322* (0.0299)	–	0.2149 (0.1913)
BAA	0.0774* (0.0244)	0.1027* (0.0215)	-0.1338* (0.0550)	5.9226*	1.6628* (0.2679)	0.9926* (0.0046)	0.0193* (0.0092)	0.1844* (0.0380)	–	0.2761* (0.1222)
BG	0.0540 (0.0283)	0.0723* (0.0220)	-0.1836* (0.0635)	8.3580*	2.3356* (0.4692)	0.9864* (0.0067)	0.0407* (0.0129)	0.0811* (0.0350)	–	0.4286 (0.3173)
Barclays	0.0734* (0.0288)	0.1262* (0.0217)	-0.1824* (0.0619)	8.6838*	3.0229* (1.0191)	0.9940* (0.0047)	0.0300* (0.0121)	0.0301 (0.0263)	0.1158* (0.0445)	0.7935* (0.0580)
Blue Circle	0.0501 (0.0327)	0.1161* (0.0253)	-0.2025* (0.0709)	8.1609*	3.3860* (1.0864)	0.9906* (0.0053)	0.0370* (0.0124)	0.0876* (0.0391)	–	0.5852* (0.1638)
British Airways	0.0934* (0.0309)	0.0901* (0.0210)	-0.1992* (0.0695)	8.2257*	2.6525* (0.5584)	0.9952* (0.0031)	0.0189* (0.0065)	0.0084 (0.0224)	0.1530* (0.0472)	0.5911* (0.1203)
CGU	0.0628* (0.0282)	0.0835* (0.0000)	-0.1944* (0.0616)	9.9594*	2.2975* (0.5147)	0.9943* (0.0044)	0.0236* (0.0089)	0.0377 (0.0247)	0.0563 (0.0329)	0.7953* (0.0776)

Table 3.9 (continued). CGARCH/ACGARCH Model Conditional Mean and Variance Specifications (Monday Effect)

Stock/Index	μ	a_1	λ_d	Wald ($\lambda_d = 0$)	ω	ρ	ϕ	α	δ_s	β
Cadbury Schweppes	0.0340 (0.0268)	0.0997* (0.0210)	-0.1061 (0.0590)	3.2351	1.9091* (0.2064)	0.9637* (0.0131)	0.0508* (0.0130)	0.1286* (0.0374)	-0.1604* (0.0500)	0.4519* (0.2060)
Enterprise Oil	0.0208 (0.0331)	0.0991* (0.0303)	-0.1216 (0.0665)	3.3424	2.0223* (0.4483)	0.9959* (0.0085)	-0.0080* (0.0025)	0.1019* (0.0366)	–	0.8274* (0.0492)
ICI	0.0419 (0.0263)	0.1169* (0.0216)	-0.1161* (0.0569)	4.1638*	2.0940* (0.8241)	0.9913* (0.0080)	0.0328* (0.0105)	0.0853* (0.0373)	–	0.3056 (0.2412)
Land Securities	0.0395 (0.0212)	0.0762* (0.0206)	-0.1013* (0.0491)	4.2601*	1.2365* (0.2410)	0.9952* (0.0034)	0.0154 (0.0094)	0.0564* (0.0174)	–	0.8458* (0.0592)
Legal & General	0.0888* (0.0289)	0.1021* (0.0219)	-0.1651* (0.0660)	6.2578*	2.5011* (0.6253)	0.9939* (0.0035)	0.0261* (0.0082)	0.0748* (0.0299)	–	0.5786* (0.2071)
Prudential	0.0904* (0.0316)	0.0754* (0.0210)	-0.1804* (0.0669)	7.2671*	2.5283* (0.3032)	0.9911* (0.0060)	0.0169* (0.0079)	0.0902* (0.0310)	–	0.6274* (0.1186)
Rio Tinto	0.0575* (0.0262)	0.1056* (0.0209)	-0.1080 (0.0561)	3.7037	1.8599* (0.3270)	0.9925* (0.0058)	0.0255* (0.0124)	0.0682* (0.0271)	–	0.7559* (0.1247)
Royal Bank of Scotland	0.0844* (0.0319)	0.1143* (0.0219)	-0.1867* (0.0777)	5.7701*	3.2238* (0.9590)	0.9945* (0.0048)	0.0242* (0.0073)	0.0867* (0.0273)	–	0.5459* (0.1639)
Standard Chartered	-0.1326* (0.0336)	0.1052* (0.0224)	0.2717* (0.0702)	14.974*	4.2680* (1.8276)	0.9941* (0.0043)	0.0424* (0.0120)	0.0978* (0.0253)	–	0.6103* (0.1266)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes significance at the 5% level. Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom.

Table 3.10. Log Likelihood Values for the ARCH Type Models				
Stock/Index	**GARCH**	**GJR**	**CGARCH**	**ACGARCH**
FTSE 100	-3,287.232	-3,280.195	–	–
Asda	-5,852.166	–	-5,813.407	–
Associated British Foods	-4,073.127	-4,058.662	-4,070.646	–
BAA	-4,457.261	–	-4,451.970	–
BAT Industries	-5004.513	–	–	–
BOC	-4,455.778	–	–	–
BG	-4,936.153	–	-4,929.083	–
BT	-4,584.309	–	-4,584.125	–
Barclays	-5,062.307	–	-5,054.114	-5,047.220
Bass	-4508.380	–	-4507.278	–
Blue Circle	-5,342.656	-5,329.980	-5,336.698	–
Boots	-4751.349	–	-4749.118	-4739.114
British Airways	-5,241.235	-5235.518	-5,235.518	-5,223.944
CGU	-4912.115	–	-4908.849	-4904.732
Cadbury Schweppes	-4,761.393	–	-4,758.563	-4,750.325
Diageo	-4790.324	-4782.137	-4782.137	–
EMI	-4,566.559	-4,553.407	-4,565.153	–
Enterprise Oil	-5,090.134	–	-5,063.702	–
General Electric	-4849.525	–	-4847.406	-4841.941
Glaxo Wellcome	-5193.716	–	-5188.384	–
ICI	-4,657.610	–	-4,648.628	–
Ladbroke	-5,555.053	-5,530.163	-5,549.076	–
Land Securities	-4,168.719	–	-4,162.461	–
Legal & General	-5,096.101	–	-5,094.725	–
Marks & Spencer	-4777.875	–	-4777.206	–
Natwest Bank	-5231.379	–	–	–
Pearson	-4,874.434	–	-4,867.110	–
Prudential	-5135.081	–	-5126.588	–
RMC	-4,828.569	–	-4,877.910	–

Table 3.10 (continued). Log Likelihood Values for the ARCH Type Models

Stock/Index	GARCH	GJR	CGARCH	ACGARCH
Rank Group	-5,068.681	–	-5,061.593	–
Reckitt & Colman	-4,235.045	–	-4,235.080	–
Reed International	-4,760.557	-4,752.243	-4,760.465	–
Reuters	-5184.456	-5174.498	-5182.457	–
Rio Tinto	-4,762.766	-4,753.370	-4,758.668	–
Royal & Sun Alliance Ins.	-5,306.650	–	–	–
Royal Bank of Scotland	-5,299.697	–	-5,297.014	–
Sainsbury	-4779.970	–	-4775.875	–
Scottish & Newcastle	-4,844.374	–	–	–
Standard chartered	-5,573.524	–	-5,557.920	–
Unilever	-4087.568	–	-4,078.124	–

Notes: The log likelihood values refer to the equation specifications shown in tables 3.2 and 3.5.

Table 3.11. Schwarz Criterion Values for the ARCH Type Models

Stock/Index	GARCH	GJR	CGARCH	ACGARCH
FTSE 100	2.375762	2.373556	–	–
Asda	4.218387	–	4.198870	–
Associated British Foods	2.943191	2.935648	2.944258	–
BAA	3.219149	–	3.218197	–
BAT Industries	3.612290	–	–	–
BOC	3.215235	–	–	–
BG	3.560332	–	3.560951	–
BT	3.310420	–	3.313137	–
Barclays	3.650960	–	3.650772	3.648669
Bass	3.255872	–	3.257930	–
Blue Circle	3.855209	3.853778	3.855850	–
Boots	3.427570	–	3.431666	3.427328
British Airways	3.782349	3.781091	3.779785	3.775626
CGU	3.545912	–	3.546415	3.546307
Cadbury Schweppes	3.434786	–	3.438451	3.435156
Diageo	3.455570	3.452538	3.453457	–
EMI	3.297668	3.291069	3.299507	–
Enterprise Oil	3.670951	–	3.657660	–
General Electric	3.498099	–	3.502275	3.501198
Glaxo Wellcome	3.745363	–	3.747230	–
ICI	3.360229	–	3.359475	–
Ladbroke	3.995009	3.992761	4.006348	–
Land Securities	3.009014	–	3.010217	–
Legal & General	3.678086	–	3.679947	–
Marks & Spencer	3.449476	–	3.451844	–
Natwest Bank	3.777268	–	–	–
Pearson	3.515994	–	3.516430	–
Prudential	3.703240	–	3.702837	–

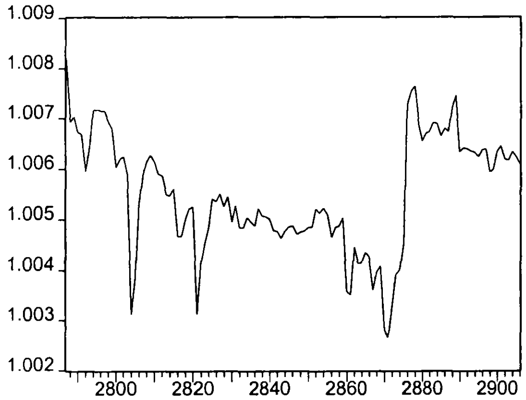
Table 3.11 (continued). Schwarz Criterion Values for the ARCH Type Models

Stock/Index	GARCH	GJR	CGARCH	ACGARCH
RMC	3.488743	–	3.524189	–
Rank Group	3.655539	–	3.656145	–
Reckitt & Colman	3.062361	–	3.062386	–
Reed International	3.437035	3.433911	3.439817	–
Reuters	3.741560	3.737255	3.742972	–
Rio Tinto	3.438622	3.434720	3.438526	–
Royal & Sun Alliance Ins.	3.826493	–	–	–
Royal Bank of Scotland	3.824348	–	3.825269	–
Sainsbury	3.448131	–	3.450887	–
Scottish & Newcastle	3.494399	–	–	–
Standard chartered	4.018214	–	4.012702	–
Unilever	2.950716	–	2.949630	–

Notes: The Schwarz criterion values refer to the equation specifications shown in tables 3.2 and 3.5.

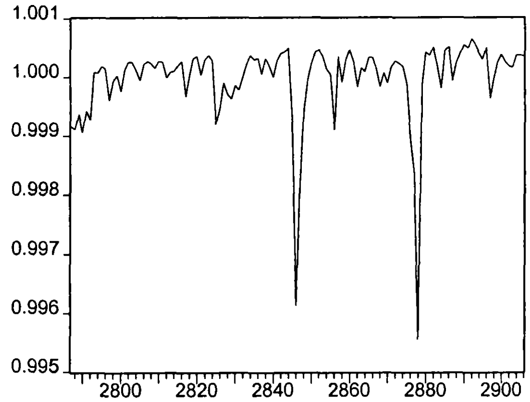
Appendix 2

Figure 4.1



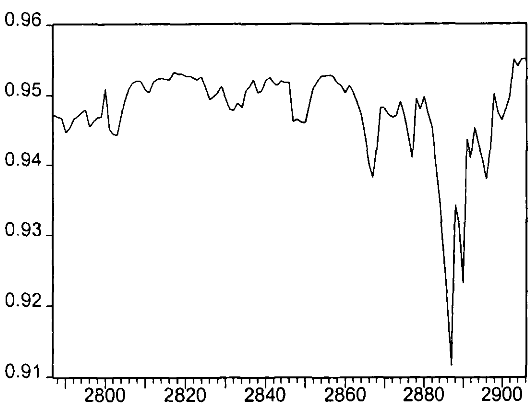
BAT Industries
GARCH model volatility persistence

Figure 4.2



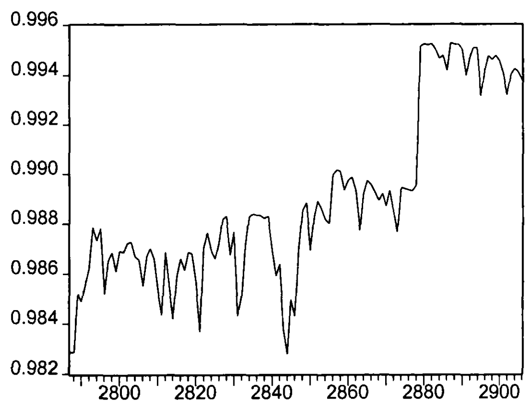
Bass
GARCH model volatility persistence

Figure 4.3



Cadbury Schweppes
GARCH model volatility persistence

Figure 4.4



Marks & Spencer
GARCH model volatility persistence

Figure 4.5

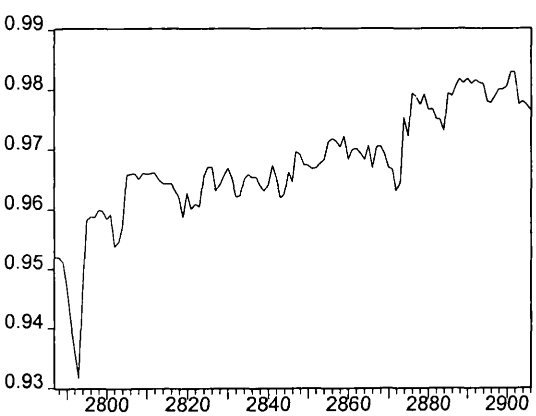
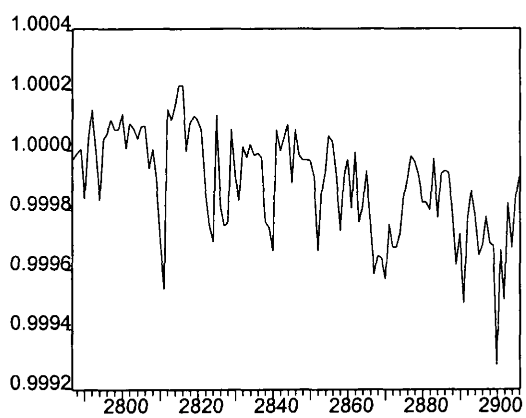


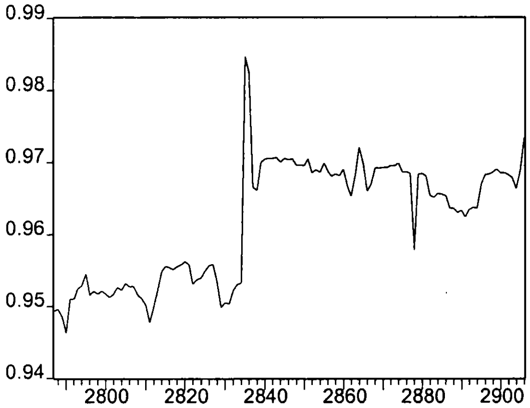
Figure 4.6



Pearson
GARCH model volatility persistence

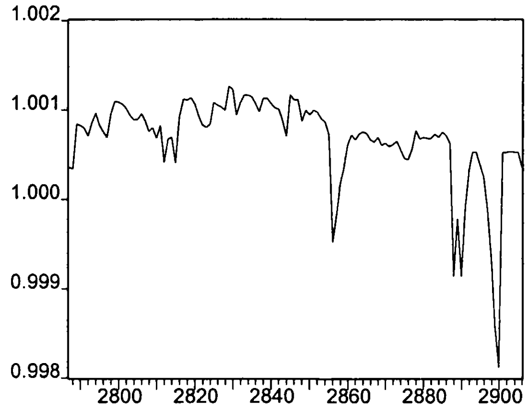
RMC
GJR model volatility persistence

Figure 4.7



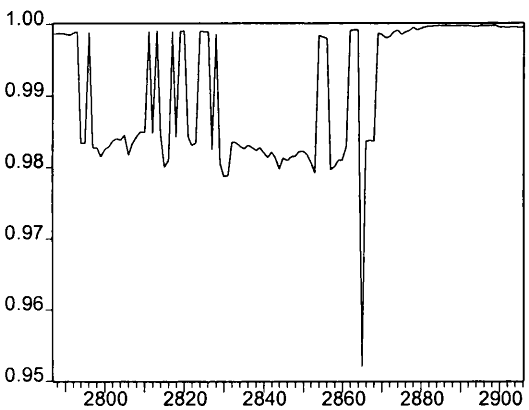
Reckitt & Colman
GARCH model volatility persistence

Figure 4.8



Royal & Sun Alliance Insurance
GJR model volatility persistence

Figure 4.9



Standard Chartered
GJR model volatility persistence

Table 4.1. Forecast Error Statistics for the GARCH/GJR Model (Recursive Equation Estimation)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise and $M_t = 1$ when the day of the week is Monday and zero otherwise. The GJR model reduces down to the GARCH model when $\gamma_1 = 0$.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
FTSE 100	RMSE	4.1373	5.5188*	2.2225*	3.1938*	3.5413	1.4488
	MAE	3.3971*	3.8737	1.9723	2.0502	2.1918*	1.2631
	MedAPE	0.7782*	1.3048	1.7433	2.4122	0.7742	3.1354
	MedSE	7.2763	8.9069	3.1237	2.1997	0.9497	2.0676
Asda	RMSE	6.9339	10.025*	5.7613	6.8596	5.6305	4.0681
	MAE	5.7783	7.8625	5.1409	5.4745	4.8291	3.4480
	MedAPE	3.3779	0.9786	1.0491	2.6015	2.0548	1.8319
	MedSE	29.960	34.692	24.645	19.232*	20.686	10.789
Associated British Foods	RMSE	9.2101	16.674	9.8000	29.476	12.848	9.3901
	MAE	7.8350	10.076*	8.4428*	21.193	10.541	8.5793
	MedAPE	0.7671*	0.8721	1.8494	0.9724	2.3134	3.2219
	MedSE	48.138	21.371	55.772	162.84	121.98	90.546
BAA	RMSE	5.7430	3.7754	5.1081	6.1370	2.7895	7.4026
	MAE	4.1643	2.9719	4.0260	3.6667	2.3502	4.4359
	MedAPE	4.0480	0.7772	0.8193*	5.0033	6.1127	5.1377
	MedSE	5.8762	5.4232	7.8216	6.6300	4.8145	5.5456
BAT Industries	RMSE	234.34	14.818	10.712	10.024	46.164	7.4525
	MAE	83.033	13.224	8.9700	6.8458	20.458	6.2510
	MedAPE	9.4842	2.4731	5.9544	0.6724	1.7134	1.4481
	MedSE	1165.0	220.39	75.264	19.765	96.282	46.997
BOC	RMSE	4.4330	7.8909	14.392	3.2609	3.5771*	8.6813
	MAE	3.6169	5.3324*	7.5670	3.0533	2.9553	4.8326
	MedAPE	0.7004	0.7104	5.2651	5.0549	3.0639	0.8425
	MedSE	11.493	15.296	26.308	9.8907	5.6109	6.3017

Table 4.1 (continued). Forecast Error Statistics for the GARCH/GJR Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
BG	RMSE	10.282	6.2217	3.0637	4.9939	12.822	7.3456
	MAE	7.2928	4.6412	2.4858	3.3041	6.7304	5.1865
	MedAPE	3.1219	0.9191	2.9468	13.184	2.1134	1.1952
	MedSE	30.555	17.777	4.4856	6.2850	10.378	17.597
BT	RMSE	7.7995	10.261	10.634	4.7023	8.6911	24.504
	MAE	5.2279	7.5450	7.9132	4.3121	6.0170	9.9735
	MedAPE	0.8487	0.7610*	0.8282	2.5290	0.8012	2.9206
	MedSE	11.001	29.424	26.661	22.057	16.335	22.274
Barclays	RMSE	23.572	21.978	16.950	8.2194	11.396	13.534
	MAE	17.873	15.351	10.572*	6.9236	8.1427	10.042
	MedAPE	1.0173	0.7570	0.7653	2.8689	2.4874	0.7769*
	MedSE	142.95	135.49	47.278	42.978	36.122	48.327
Bass	RMSE	37.926*	13.678	19.779	8.2877	18.214	11.124
	MAE	18.946*	9.2395	13.087	7.2213	10.827	8.6503
	MedAPE	0.9561	2.3035	1.0834	2.6084	2.0696	4.0103
	MedSE	62.661	52.237	66.843	52.600	48.336	58.527
Blue Circle	RMSE	20.890	9.5981	6.8669	4.3013	7.1607	12.133
	MAE	16.587	8.8392	6.2360	3.9978	5.4399	8.1629*
	MedAPE	1.8327	1.3806	4.8121	4.3664	2.5384	0.8117
	MedSE	240.83	88.224	43.121	14.124	16.077	21.570
Boots	RMSE	3.6740*	4.1214	18.183	4.7918	10.543	6.3972
	MAE	2.7396	3.5099	8.4938	4.1639	6.1896	5.2342
	MedAPE	0.8701	0.6942	4.3106	2.1661	1.2043	3.5409
	MedSE	4.8354	11.175	21.682	13.319	11.174	18.885
British Airways	RMSE	18.948*	14.174	11.268	8.9302	8.5447*	6.5905*
	MAE	14.711	10.457	9.0614	6.7170	6.3049	5.9334
	MedAPE	0.7852*	0.5688*	4.1698	1.7282	1.2191	1.0475
	MedSE	126.05	60.700	71.240	31.826	31.824	36.507

Table 4.1 (continued). Forecast Error Statistics for the GARCH/GJR Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
CGU	RMSE	28.093	32.987	18.137	10.396*	8.7478	5.5756*
	MAE	19.262	20.095	13.319	8.8816	6.4025*	4.3195
	MedAPE	0.7789*	3.7252	1.4755	4.0486	0.8164	0.5725*
	MedSE	153.06	181.82	97.802	68.021	29.535	20.548
Cadbury Schweppes	RMSE	6.9929	15.004	2.5463	7.6916	5.5052	6.8526
	MAE	4.1693	10.379	2.3613	4.9596	3.9830	4.2998
	MedAPE	0.9121	0.8780*	2.1467	3.0359	2.9184	1.7005
	MedSE	7.4628	48.912	4.9306	10.089	5.8640	6.9533
Diageo	RMSE	28.414*	17.572*	11.168*	14.951	8.7132	8.1532
	MAE	18.093	13.343	7.4856	11.428	6.8775	6.5625
	MedAPE	1.1084	2.8008	1.1702	1.0590	6.6829	2.9384
	MedSE	96.776	118.07	36.672	76.952	36.298	29.921
EMI	RMSE	63.612	14.015	52.484*	10.008	8.1761	17.085
	MAE	28.423	12.726	21.473	9.6298	6.9030	10.983
	MedAPE	1.1652	4.7096	3.7724	16.098	4.0325	4.3747
	MedSE	177.76	177.05	130.02	110.29	52.812	40.029
Enterprise Oil	RMSE	26.421	9.6108	9.4324	5.7950	10.967*	6.5448
	MAE	22.429	8.2816	8.3191	4.8268	5.2974	5.2452
	MedAPE	3.3787	2.0261	0.5968*	6.9337	0.7474	1.1567
	MedSE	415.78	71.619	74.123	16.018	6.8309	19.889
General Electric	RMSE	17.583*	11.652*	8.2616	31.270	9.3536	6.9035
	MAE	10.389	8.9669	5.9503	17.250	6.6219	5.0921
	MedAPE	0.7477	4.7399	1.0025	3.0672	0.8314	2.3603
	MedSE	87.118	52.225	20.445	79.493	23.445	17.541
Glaxo Wellcome	RMSE	7.8758	13.613	3.0959	3.4682	5.9266	5.6862
	MAE	5.1629	8.6196	2.5396	2.6927	4.0938	3.8464
	MedAPE	0.8973	6.7195	5.1675	1.3156	1.2685	0.7091
	MedSE	12.164	32.484	5.8759	6.2834	6.7729	11.210

Table 4.1 (continued). Forecast Error Statistics for the GARCH/GJR Model (Recursive Equation Estimation)							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
ICI	RMSE	16.790	37.026*	8.9086	7.8517*	16.683	16.757
	MAE	11.546	25.942	7.6534	7.3701	11.229	10.728
	MedAPE	1.0537	1.5304	2.5159	9.5180	2.2082	2.8985
	MedSE	80.082	220.42	78.760	53.421	46.855	71.637
Ladbroke	RMSE	27.915	13.058*	23.014*	9.3839*	14.723	51.277
	MAE	17.862	10.676	14.910	8.4940	10.531	18.828
	MedAPE	0.8107	1.0924	1.4375	2.2099	4.5649	1.2393
	MedSE	102.09*	93.473	81.703	68.094	56.177	33.527
Land Securities	RMSE	3.7233	3.3310	2.5509	1.8971	4.2087	5.0415
	MAE	2.7324	2.7732	1.7690	1.5158	2.7798	2.9095
	MedAPE	1.9920	2.0895	0.7469	1.2631	1.5607	6.6150
	MedSE	4.0513	5.4037	1.5679	1.7577	2.9393	4.4538
Legal & General	RMSE	34.109*	32.005	10.070	9.3060	17.317	9.8175
	MAE	19.486	18.044	9.0423	7.1459	9.0787	8.1154
	MedAPE	2.6186	1.4299	1.4153	1.1167	1.8330	2.8647
	MedSE	55.960	121.04	96.348	39.591	43.594	46.784
Marks & Spencer	RMSE	11.666	7.1843	25.670	9.4596*	47.851	6.2016
	MAE	7.4316	4.7723	12.296	6.2065	15.661	5.9944
	MedAPE	0.8427*	1.2327	2.4822	3.8165	1.0132	20.152
	MedSE	18.707	11.847	43.047	26.732	18.422	33.879
Natwest Bank	RMSE	14.899	21.845	10.993*	8.3521*	20.888	13.589
	MAE	9.3883*	15.627	7.7329	6.3169	11.141	9.0237
	MedAPE	0.7838*	1.9980	1.1029	1.0119	1.4174	0.8350
	MedSE	52.376	124.11	50.302	33.735	26.388	40.417
Pearson	RMSE	19.066	6.6815	4.6750	6.1918	6.8197	7.8858
	MAE	11.737	5.3142	3.9363	4.7993	4.2516	5.7853
	MedAPE	0.8145	0.8956	0.7441*	1.5935	1.3106	3.5508
	MedSE	34.223	19.308	13.673	13.504	9.3637	13.669

Table 4.1 (continued). Forecast Error Statistics for the GARCH/GJR Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Prudential	RMSE	32.719	26.769*	8.0695*	5.5351	9.0128	8.5361
	MAE	13.237	14.443	5.4275	4.2329	5.2563	5.9548*
	MedAPE	0.9196	0.8297	1.1633	2.7018	1.2712	0.6696*
	MedSE	16.849	72.654	15.048	11.798	6.7710	15.471
RMC	RMSE	34.284	14.243*	6.8197	7.3244	15.521	14.349
	MAE	19.237*	10.979	6.4900	5.0663	9.0705	8.8801
	MedAPE	1.6722	3.8024	14.461	9.8879	1.3098	4.2216
	MedSE	111.55	101.26	42.963	18.803	32.276	29.907
Rank Group	RMSE	21.621	16.148	19.531	9.9589	14.371	24.382
	MAE	13.754	12.618	9.2813	8.5358	7.6709	11.254
	MedAPE	0.8060*	2.0369	0.8550	2.1687	1.0304	0.9773
	MedSE	74.244	94.702	20.496	78.880	23.306	30.727
Reckitt & Colman	RMSE	13.622*	5.8082	53.849	3.9333	6.1047	16.879
	MAE	7.3286	3.7746*	17.828	3.4330	4.3302*	8.4411
	MedAPE	4.6599	0.6938*	4.9400	10.327	0.8224*	2.4873
	MedSE	13.582	6.1896	14.157	9.1600	8.6951	18.168
Reed International	RMSE	10.831	7.4505	5.7422*	14.110	10.066	14.874
	MAE	7.6235	5.6229	4.8516	7.9652	6.6592	8.7700
	MedAPE	1.4523	0.8305	0.7638	2.2246	6.6565	1.3556
	MedSE	19.988	22.261	22.589	21.848	16.132	16.492
Reuters	RMSE	39.583	28.043	6.4638	13.339	29.171	8.2207
	MAE	21.641	20.324	5.7290	8.5934	14.001	6.0232*
	MedAPE	0.9220*	0.9754	3.4807	0.9563	1.1368	0.5628
	MedSE	56.504	184.59	29.369	25.116	13.085	16.144
Rio Tinto	RMSE	9.7102	5.6112*	3.6852	4.6598	4.4222*	7.3766
	MAE	7.6405	4.4329	3.0361	3.5503	3.0414	4.8423
	MedAPE	1.4560	0.8498*	1.4042	2.6022	1.1066	2.5697
	MedSE	26.739	18.635	9.8696	8.7321	5.4730	8.5783

Table 4.1 (continued). Forecast Error Statistics for the GARCH/GJR Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Royal & Sun Alliance Ins.	RMSE	40.434	23.214*	21.108	10.377	14.249*	11.025
	MAE	21.959	17.235	14.254	10.154	8.5846	9.3117
	MedAPE	0.8278	1.7272	2.0882	8.2702	0.6414	10.166
	MedSE	98.952	150.93	146.94	112.90	36.015	74.426
Royal Bank of Scotland	RMSE	18.641*	15.584	14.811	12.867	15.311*	8.1559*
	MAE	12.269	10.528	10.588*	9.7530	10.478	6.0924*
	MedAPE	0.9380	0.9729	0.5982	3.6948	8.1043	0.7608
	MedSE	56.655	66.518	75.150	81.986	56.802	29.160
Sainsbury	RMSE	10.449	9.9077	4.2037	6.4016	10.203	16.917
	MAE	5.1967	5.0449	3.5097	4.3796	5.0779	6.2262
	MedAPE	2.2077	0.9464	0.7069	1.4891	4.7633	2.3202
	MedSE	10.804	7.8721	10.312	12.458	10.215	6.6879
Scottish & Newcastle	RMSE	9.4875*	17.834	7.0757	10.172	10.267*	5.3626
	MAE	5.8504	9.8909	5.1768	7.5609	7.9787	4.4414
	MedAPE	1.2659	3.5080	4.4730	1.0082	0.9537	3.6152
	MedSE	16.004	39.714	15.936	40.010	58.889	17.250
Standard Chartered	RMSE	22.289	29.514	14.734	9.6964	44.317	11.636
	MAE	17.321	22.546	11.579	7.7248	24.504	10.525
	MedAPE	1.1729	1.5275	1.2187	1.6888	2.8351	4.2682
	MedSE	255.17	315.23	124.49	51.023	160.04	107.09
Unilever	RMSE	19.251	18.825*	8.4427	5.5816*	10.677	13.468
	MAE	11.043	11.560	5.7698	4.4679	7.1851*	8.2741
	MedAPE	0.8332	2.6621	2.6563	1.4049	0.8526	2.3249
	MedSE	25.254	55.795	25.204	15.876	17.239	23.449

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 4.2. Forecast Error Statistics for the CGARCH/ACGARCH Model (Recursive Equation Estimation)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t,\ h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$
$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Asda	RMSE	7.0190	10.358	5.4058	7.0335	5.5919	4.0138
	MAE	5.3712	7.8723	4.5357	5.6576	4.7125*	3.2627*
	MedAPE	2.7059	0.8457	0.6476*	3.0683	1.8846	1.6986
	MedSE	18.885	37.619	17.576	23.800	16.974	9.1801
Associated British Foods	RMSE	9.1953*	16.582	9.7738*	29.152	12.439*	7.9153
	MAE	7.9052	10.301	8.5469	21.024	10.076	7.0146
	MedAPE	0.8387	0.9511	1.9352	0.9704	2.1082	2.5246
	MedSE	45.021	28.279	65.605	178.74	85.609	51.748
BAA	RMSE	5.7357	3.8246	5.1356	6.0716*	2.7424	7.4181
	MAE	4.0966	3.0254	4.0456	3.5601	2.2919	4.3783
	MedAPE	3.8183	0.7937	0.8275	4.7415	6.1467	5.1254
	MedSE	6.1142	5.3818	7.5353	5.6997	4.4062	5.4571
BG	RMSE	10.045*	6.0566*	3.3083	5.0485	12.888	7.1905*
	MAE	7.1441	4.6573	2.8707	3.4184	6.9075	5.0192
	MedAPE	3.2940	0.9954	3.8557	13.772	2.4454	1.0617
	MedSE	28.030	17.810	6.5588	6.3787	12.427	14.078
BT	RMSE	7.7841	10.260*	10.642	4.6864*	8.5764*	24.492
	MAE	5.2159	7.5078*	7.9130	4.2757	5.9730*	9.9585
	MedAPE	0.8463	0.7615	0.8237	2.4470	0.7737*	2.7948
	MedSE	10.912	28.997	25.837	20.837	16.534	21.760
Barclays	RMSE	23.812	21.159*	17.377	8.6819	11.533	13.590
	MAE	17.996	14.650*	10.723	7.3893	8.4416	10.039
	MedAPE	1.1334	0.5770*	0.7583*	2.4831	2.5651	0.7865
	MedSE	162.06	121.64	34.858	47.891	47.458	49.397

Table 4.2 (continued). Forecast Error Statistics for the CGARCH/ACGACRH Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Bass	RMSE	38.190	13.594*	19.767	8.0233*	18.213	10.929*
	MAE	19.145	9.1360	12.656	6.7714	10.361	8.1786
	MedAPE	1.0962	2.1599	0.9688	2.2770	1.7410	3.4413
	MedSE	79.963	48.868	56.172	41.621	37.767	45.925
Blue Circle	RMSE	21.013	9.4139*	6.6818	4.2767	7.1559*	12.111*
	MAE	16.016*	8.6890	6.0727	3.9470	5.3855	8.3577
	MedAPE	1.4759	1.1434	4.2269	4.5005	2.5327	0.8162
	MedSE	172.82	78.493	36.493	15.050	16.245	24.612
Boots	RMSE	3.7168	4.2134	18.414	4.7819*	10.542	6.4529
	MAE	2.6410	3.5287	8.9611	4.1469	6.2457	5.1780
	MedAPE	0.7362	0.6986	5.3692	2.3115	1.1517	3.3732
	MedSE	4.0876	8.2843	22.938	11.857	10.741	18.172
British Airways	RMSE	19.887	14.811	11.035*	8.8603*	8.6919	6.8052
	MAE	15.386*	10.345*	8.4333	6.5882	6.3228	6.0643
	MedAPE	0.8593	0.6058	3.4647	1.3059	1.4327	0.7669*
	MedSE	138.54	52.297*	55.422	33.378	28.082	35.212
CGU	RMSE	28.462	32.032*	18.058	10.749	8.5062	5.7373
	MAE	18.993	18.828	12.954	9.4309	6.4688	4.5606
	MedAPE	0.8148	2.7102	1.3239	4.7700	0.7688*	0.5870
	MedSE	104.30	149.74	88.925	74.769	29.521	21.236
Cadbury Schweppes	RMSE	7.0819	15.382	2.7262	7.6238*	5.4563*	6.7699*
	MAE	4.2936	10.418	2.5083	5.0792	3.7647	4.2906
	MedAPE	0.8889*	0.9866	2.3564	2.7072	2.2775	1.5044
	MedSE	7.0808	44.619	5.6633	10.511	5.2845	6.7622
Diageo	RMSE	29.403	18.034	11.210	14.976	8.7582	7.7940*
	MAE	18.112	13.062	7.6460	11.533	6.9236	6.2466
	MedAPE	1.0128	2.5767	1.1541	1.2814	6.7690	3.1665
	MedSE	72.898	92.495	37.333	68.203	34.341	24.762

Table 4.2 (continued). Forecast Error Statistics for the CGARCH/ACGACRH Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
EMI	RMSE	63.303*	12.455	53.617	9.8066	7.8902	17.016
	MAE	28.098*	10.801	22.185	9.3150	6.4474	11.463
	MedAPE	1.4944	3.0500	2.3911	14.221	3.7046	5.3588
	MedSE	188.70	102.53	74.114	77.722	40.768	50.457
Enterprise Oil	RMSE	26.365*	6.9927	10.131	5.4907*	11.313	6.3750*
	MAE	19.341	5.4171	8.1533	3.4516*	5.3644	4.8480
	MedAPE	1.2775	0.8163	0.7702	3.1188	0.8379	0.8206
	MedSE	234.49	17.988	41.062	3.7460	3.0613*	15.162
General Electric	RMSE	17.606	11.721	8.3453	31.940	9.1686*	6.9120
	MAE	10.836	8.9641	6.0690	17.987	6.5593*	5.1154
	MedAPE	0.7213*	4.3608	0.8833	3.3191	0.7833	2.6145
	MedSE	76.857	49.835	26.208	72.155	24.319	17.950
Glaxo Wellcome	RMSE	7.8098	13.493*	3.1466	3.5463	5.8455	5.6512
	MAE	5.2068	8.4288	2.6743	2.9312	4.1565	3.8348
	MedAPE	0.9348	6.2545	6.4601	1.8170	1.4937	0.7009
	MedSE	12.959	29.695	8.2059	7.4947	8.7874	12.549
ICI	RMSE	17.041	37.041	8.1562*	8.0990	16.489	16.602*
	MAE	11.601	25.231	7.1052	7.6076	11.404	9.7675
	MedAPE	0.8638*	1.2462	2.1822	10.009	2.9031	2.5392
	MedSE	69.277	162.61	68.719	52.413	39.271	46.315
Ladbroke	RMSE	27.823*	13.121	23.906	9.7611	14.578	51.953
	MAE	17.722	10.603	16.124	8.7832	10.775	22.759
	MedAPE	0.8428	1.0577	1.1978	2.7375	6.0276	2.1543
	MedSE	150.11	78.588	101.07	76.189	55.083	74.189
Land Securities	RMSE	3.7462	3.3409	2.5625	1.9125	4.1569	5.0537
	MAE	2.6849	2.7944	1.7807	1.5592	2.7844	2.9029
	MedAPE	1.9824	2.3198	0.7724	1.3974	1.7105	6.3323
	MedSE	3.6556	5.0267	1.6626	1.9587	3.2368	4.2870

Table 4.2 (continued). Forecast Error Statistics for the CGARCH/ACGACRH Model (Recursive Equation Estimation)							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Legal & General	RMSE	34.141	32.146	9.8379*	9.2325*	17.351	9.7408*
	MAE	19.218	18.073	8.6767	6.8887	9.0631	7.9992
	MedAPE	2.3256	1.2100	1.1786	1.0485	1.7030	2.7370
	MedSE	54.727	106.09	89.749	31.972	42.258	44.296
Marks & Spencer	RMSE	11.717	7.1684	25.660	9.4854	47.823	6.2957
	MAE	7.4702	4.7488	12.272	6.2560	15.513	6.0787
	MedAPE	0.8489	1.2655	2.2975	3.6840	1.0255	20.479
	MedSE	18.537	11.528	41.901	26.089	18.249	34.506
Pearson	RMSE	18.849	6.5316*	4.6123*	6.1467*	6.7735*	7.9052
	MAE	11.622*	5.1799	4.0776	4.9745	4.4420	5.9556
	MedAPE	0.7920	0.8403	0.8997	1.9180	1.8666	4.0362
	MedSE	29.691	24.540	12.929	18.020	12.495	15.416
Prudential	RMSE	32.676*	27.307	8.2308	5.6038	8.8416*	8.6635
	MAE	13.287	14.090*	5.8672	5.0096	5.5519	6.0645
	MedAPE	0.9217	0.8175*	1.6276	4.1996	1.2827	0.6899
	MedSE	16.703	60.943	16.755	21.267	13.254	15.026
RMC	RMSE	34.011*	14.326	7.2625	7.6090	15.270*	14.180*
	MAE	19.928	11.079	6.9385	5.9170	8.9737*	9.0354
	MedAPE	1.8299	3.8672	15.832	12.750	1.2209	4.2063
	MedSE	145.82	94.752	51.479	31.801	38.417	32.162
Rank Group	RMSE	21.727	16.258	19.498	9.6011*	14.827	24.704
	MAE	13.792	12.393	9.3236	8.2718	8.5690	11.812
	MedAPE	0.8949	2.1355	1.0180	1.9567	1.1004	1.0012
	MedSE	75.772	74.274	22.095	58.388	33.129	25.764
Reed International	RMSE	10.778	7.4976	5.8130	14.053	10.159	14.679*
	MAE	7.9354	5.7126	4.8997	8.0430	7.1554	9.2302
	MedAPE	1.6523	0.8388	0.7437	2.1736	7.9370	2.2840
	MedSE	26.145	25.212	22.006	23.453	21.749	26.856

Table 4.2 (continued). Forecast Error Statistics for the CGARCH/ACGACRH Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Reuters	RMSE	39.749	28.159	7.7656	13.255*	28.749	7.9734*
	MAE	22.104	20.519	6.9537	9.2047	14.837	6.1163
	MedAPE	1.0657	0.8999*	4.7141	1.3559	1.8177	0.4830*
	MedSE	70.016	213.44	57.877	42.049	27.855	32.003
Rio Tinto	RMSE	9.7062	5.7518	3.6377	4.6572*	4.4875	7.3054
	MAE	7.8104	4.4953	2.9604	3.5737	3.1374	5.0984
	MedAPE	1.6829	1.0203	1.3945	2.4314	1.0636	3.4656
	MedSE	34.386	17.797	8.1584	8.8731	6.8182	12.654
Royal & Sun Alliance Ins.	RMSE	40.364*	23.233	21.063	9.0979	14.341	10.798
	MAE	21.740*	16.320	13.699	8.9616	8.2776*	8.9494
	MedAPE	0.8362	1.4265	1.7121	7.2126	0.6347*	9.0566
	MedSE	96.218	110.73	109.30	85.352	27.739	62.451
Royal Bank of Scotland	RMSE	18.817	14.816*	15.214	12.613*	15.467	8.2315
	MAE	12.345	9.5258	10.938	9.3348	10.454	6.1753
	MedAPE	0.9397	0.8945	0.6173	3.5302	8.2391	0.7772
	MedSE	57.808	44.076	67.330*	62.567	54.639	29.937
Sainsbury	RMSE	10.331	10.027	4.2685	6.5216	10.233	16.894
	MAE	4.9324	5.2492	3.5320	4.4689	5.2273	6.1168
	MedAPE	2.2594	0.8982	0.6459*	1.3730	4.8735	2.2711
	MedSE	11.513	7.5608	10.803	12.374	10.024	6.1035
Standard Chartered	RMSE	23.012	29.101*	14.609*	9.7950	44.789	10.545
	MAE	17.572	21.788	11.180	8.1097	25.415	9.2861
	MedAPE	1.0581	1.1747	1.3033	1.8294	3.2988	3.5143
	MedSE	186.02	278.23	114.69	58.364	197.39	90.391
Unilever	RMSE	19.096*	19.011	8.3393*	5.6016	10.654	13.613
	MAE	10.559*	10.911	5.3784	4.4995	7.3437	8.4673
	MedAPE	0.8020	2.2652	2.2366	1.5056	0.8427	2.7130
	MedSE	14.168	43.732	17.681	15.708	23.907	22.720

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 4.3. Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

The historical mean volatility forecast is expressed as:

$$h_{t+1} = \bar{s}_t^2 = \frac{1}{t}\sum_{j=1}^{t} s_j^2$$

where s_t^2 is the true volatility.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
FTSE 100	RMSE	5.0555	6.4781	2.3466	3.2274	3.8459	1.1852*
	MAE	3.4702	3.5371*	1.5285*	1.4708*	2.3151	0.8985*
	MedAPE	0.9121	0.8414*	0.8604*	0.9024*	0.7677*	1.3482
	MedSE	2.1103*	0.4354*	0.4677*	0.4078*	0.5451*	0.5228*
Asda	RMSE	6.6220*	10.307	4.9741*	6.6675*	5.3312*	4.2930
	MAE	5.1315*	7.5214*	4.0713*	5.2031*	4.7311	3.7890
	MedAPE	1.9004	0.7829*	0.6674	2.5471	2.4486	2.5835
	MedSE	21.719	25.156*	18.268	19.335	21.028	16.578
Associated British Foods	RMSE	11.371	19.241	12.742	32.726	14.290	7.1931*
	MAE	7.7507*	10.791	8.7008	19.919*	8.7797*	4.1964*
	MedAPE	0.8525	0.8622*	0.9204*	0.9622	0.8621*	0.7981*
	MedSE	15.821*	8.4898*	24.246*	80.562*	13.623*	3.1501*
BAA	RMSE	5.7742	4.0590	5.4995	6.3236	2.4715*	7.5745
	MAE	3.4502*	2.8907*	3.5767*	3.1811*	1.8366*	3.9851*
	MedAPE	1.1765*	0.7842	0.8657	2.7570	3.6108	2.6470
	MedSE	2.2461*	2.2738*	2.3477*	2.5616	2.3506*	2.5705*
BAT Industries	RMSE	231.71	13.999	9.0355*	10.248	47.390	4.8126*
	MAE	58.046*	9.1055*	4.7192*	6.8105	18.952*	3.6082*
	MedAPE	0.7259*	0.8179	0.9941*	0.6937	0.9073*	0.6179*
	MedSE	7.8528*	16.255*	7.6919*	9.5345*	15.155*	7.2775*
BOC	RMSE	5.1214	9.1785	14.959	2.0186*	3.6078	9.0665
	MAE	3.5833*	6.0667	6.2284*	1.5537*	2.6501*	4.7636*
	MedAPE	0.7903	0.8455	0.9256*	1.4871	1.6640	0.8078*
	MedSE	2.5877*	7.6131*	2.6850*	1.5350	2.5893*	2.7571*

Table 4.3 (continued). Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
BG	RMSE	10.770	6.6674	2.7925*	4.8706*	12.834	7.7045
	MAE	6.2618*	3.9271*	2.1558*	3.0210*	5.9609*	4.7338*
	MedAPE	1.0253	0.7486*	2.2832	9.1492	1.4057	0.8415*
	MedSE	4.6852*	4.3574*	3.1186	4.8700	4.2923*	4.8885*
BT	RMSE	8.3085	11.830	12.345	5.1245	9.9299	24.894
	MAE	4.7471*	7.7835	8.0820	3.2337*	6.2338	8.7843*
	MedAPE	0.7761*	0.9139	0.8704	0.7538*	0.8526	0.9301*
	MedSE	2.1017*	6.7423*	7.2575*	3.1503*	6.1171*	3.4819*
Barclays	RMSE	27.887	27.666	19.125	7.1893*	11.886	15.152
	MAE	17.793*	17.616	11.236	4.4049*	7.1507*	9.7304*
	MedAPE	0.9291*	0.9011	0.7747	0.8086*	1.1251	0.8651
	MedSE	38.543*	120.36*	21.561*	6.7123*	8.3482*	8.0615*
Bass	RMSE	40.854	14.708	21.414	8.4022	19.003	12.057
	MAE	19.210	7.6989*	11.285*	4.9393*	8.2707*	6.3754*
	MedAPE	0.8649*	0.8736*	0.8573*	0.8352*	0.7802*	0.9453*
	MedSE	17.760*	3.3680*	4.2565*	3.6280*	3.9025*	4.1695*
Blue Circle	RMSE	23.083	10.652	5.7047*	3.6404*	7.4743	13.330
	MAE	13.866	7.7129*	4.1674*	3.0765*	5.4794	8.2343
	MedAPE	0.9078*	0.8129*	1.3335*	2.7680	1.4811	0.8471
	MedSE	11.358*	10.515*	9.1148*	8.1053*	11.611	11.195*
Boots	RMSE	3.9343	4.5329	18.289	5.1633	11.085	6.9062
	MAE	2.5051*	3.4335*	6.8898*	3.5286*	6.1509*	4.5918*
	MedAPE	0.6679*	0.8043	1.3763	0.8554	0.9120*	1.0807
	MedSE	2.2063*	3.3980*	3.5341	3.6548*	3.8864*	3.7465*
British Airways	RMSE	22.621	18.372	11.161	9.4207	9.5861	7.2264
	MAE	15.009	13.020	5.8655*	5.5066*	6.0811*	5.4691*
	MedAPE	0.9200	0.8256	0.8431*	0.7751*	0.8017*	0.8408
	MedSE	32.987*	108.08	7.6544*	4.8235*	9.1229*	9.0339*

Table 4.3 (continued). Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
CGU	RMSE	32.288	36.064	20.191	10.651	9.7400	5.9338
	MAE	20.065	16.160*	11.650*	5.5359*	6.5147	4.2391*
	MedAPE	0.9323	0.8528*	0.8742*	0.8893*	0.7774	0.7585
	MedSE	89.656*	4.9154*	5.9771*	6.0975*	7.6369*	6.6723*
Cadbury Schweppes	RMSE	7.1590	16.475	2.0341*	7.7426	5.4773	6.9647
	MAE	4.1039*	9.6234*	1.7475*	4.3911*	3.5490*	4.0226*
	MedAPE	0.9128	0.9090	0.6475*	1.3493*	1.6333	1.2399
	MedSE	3.8730*	7.0982*	2.2048	3.9722*	4.1946*	2.8545*
Diageo	RMSE	32.786	19.500	12.185	17.086	8.4051*	8.7273
	MAE	18.695	9.7211*	6.2185*	10.586*	4.3767*	5.3516*
	MedAPE	0.8064*	0.9335*	0.7794*	0.9302*	1.7932	0.9934
	MedSE	37.289*	4.3541*	3.2167*	6.5594*	4.1010*	4.8607*
EMI	RMSE	66.169	11.778*	55.101	4.9267*	7.8610*	18.055
	MAE	28.381	6.3203*	18.700*	2.6779*	4.5160*	8.9321*
	MedAPE	0.9291	0.8927	0.8692*	2.5940	0.8947*	0.9396*
	MedSE	81.649*	2.8470*	3.5458*	2.9327	4.1953*	4.5486*
Enterprise Oil	RMSE	30.245	6.7788*	11.437	5.6106	11.145	6.5324
	MAE	18.115*	4.5256*	8.0797*	3.8278	5.1526*	4.4779*
	MedAPE	0.9055*	0.7020*	0.8038	2.9669	0.7431*	0.7789*
	MedSE	10.612*	7.2372*	17.012*	6.7937	8.0470	7.8382*
General Electric	RMSE	19.367	12.992	8.9834	32.287	10.660	6.7586*
	MAE	10.253*	6.6625*	5.5174*	14.048*	6.6554	3.9262*
	MedAPE	0.8827	0.9391*	0.8498*	0.9738*	0.7756*	0.8923*
	MedSE	26.693*	3.0542*	3.9688*	4.9185*	7.6178*	4.8329*
Glaxo Wellcome	RMSE	8.0954	14.003	2.7020	3.3737*	5.8907	5.8134
	MAE	4.7460*	6.6614*	2.2384	2.6233*	3.9127*	3.5283*
	MedAPE	0.8943*	2.0661	4.5439	1.4338	0.9455*	0.7159
	MedSE	5.7342*	6.1744*	5.6095	5.5148	6.7820*	6.4119*

Table 4.3 (continued). Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
ICI	RMSE	18.867	41.547	8.8146	7.9773	18.235	17.722
	MAE	10.476*	23.889*	5.8950*	4.8173*	10.438*	7.6972*
	MedAPE	0.8981	0.9563*	0.8508*	2.0319*	0.8885*	0.9012
	MedSE	5.2111*	19.439*	4.2894*	3.8908*	4.5879*	4.8262*
Ladbroke	RMSE	31.198	14.649	25.368	10.115	14.555	51.599
	MAE	19.239	9.6513*	13.115*	7.5069*	8.2578*	16.115*
	MedAPE	0.8584	0.8389*	0.7252*	0.8472*	1.6421	0.6560*
	MedSE	106.88	13.729*	14.568*	15.593*	15.417*	8.9298*
Land Securities	RMSE	3.8161	3.5084	2.5745	1.8773*	4.3153	5.1124
	MAE	2.1944*	2.5300*	1.4788*	1.3250*	2.7262	2.5850*
	MedAPE	0.8935*	1.2060	0.6384*	0.7903	0.8987*	2.6666
	MedSE	1.3194*	1.5727*	1.0199*	0.9915	1.5562	1.4249*
Legal & General	RMSE	36.460	34.147	10.960	9.5042	17.476	9.9674
	MAE	18.189*	16.076*	7.2326*	5.2972*	6.8623*	6.0276*
	MedAPE	0.9725*	0.8675	0.7831*	0.6436*	0.7586*	0.8931*
	MedSE	5.7177*	8.3675*	9.0432*	8.3921*	8.5258*	8.5404*
Marks & Spencer	RMSE	12.137	7.5139	25.971	10.293	48.082	3.5430*
	MAE	6.9896*	4.0397*	10.143*	5.6383*	13.925*	2.5597*
	MedAPE	0.9017	0.8255*	0.9095*	0.8990*	0.7614*	5.4128
	MedSE	3.7734*	3.5367*	4.1668*	4.3125*	4.4093*	3.9372
Natwest Bank	RMSE	16.599	24.032	11.812	9.0340	21.734	14.886
	MAE	9.7020	12.612*	6.9627*	6.1496*	10.869*	8.9787*
	MedAPE	0.8050	0.7101*	0.8224*	0.8133*	0.8958*	0.8205*
	MedSE	17.335*	7.0457*	11.411*	12.238*	9.8183*	10.051*
Pearson	RMSE	20.763	7.2494	5.0522	6.6086	6.8573	8.0569
	MAE	12.117	4.8629*	3.7196*	4.4937*	3.8684*	5.0781*
	MedAPE	0.8752	0.7181*	0.7789	0.8798*	0.9977*	1.4012
	MedSE	21.670*	6.7306*	4.4298*	5.3823*	5.3391*	4.7497*

Table 4.3 (continued). Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Prudential	RMSE	33.776	30.313	8.3239	5.4818*	9.0709	9.4467
	MAE	13.307	14.381	4.8389*	3.7863*	4.8272*	6.2414
	MedAPE	0.8452	0.8919	0.7580*	1.0438	0.8948*	0.7321
	MedSE	8.8005	8.6331*	5.6975*	5.7734	4.9766*	7.2037*
RMC	RMSE	37.305	15.166	4.7132*	6.7308*	16.656	14.779
	MAE	19.296	8.1105*	3.2404*	3.4625*	9.0146	6.8296*
	MedAPE	0.9386	0.8702*	3.6181	4.2917	0.8839	0.9391*
	MedSE	16.018	5.6371*	5.7370*	5.6542	6.4940*	3.8598*
Rank Group	RMSE	23.771	17.958	20.061	10.670	14.675	24.972
	MAE	13.635*	11.116*	8.3440*	6.5873*	6.9680*	10.702*
	MedAPE	0.8623	0.8926*	0.7616*	0.9016*	0.8593*	0.8622*
	MedSE	24.381*	6.5055*	4.1807*	6.6384*	7.4993*	7.6509*
Reckitt & Colman	RMSE	14.346	6.5056	53.139	2.4562*	6.5411	17.454
	MAE	5.9530*	3.8384	13.451*	1.7741*	3.8882	7.1184*
	MedAPE	0.9645*	0.7451	1.0492	3.4309	0.8715	0.9214*
	MedSE	1.1722*	1.7702*	1.8422*	2.1494	2.3099*	2.2455*
Reed International	RMSE	11.619	8.3206	6.4369	14.628	9.9657*	16.006
	MAE	6.0514*	5.2325*	4.2847*	6.9891*	4.7576*	8.1259*
	MedAPE	0.7245*	0.7040*	0.7362*	0.8984*	2.6350	0.9051
	MedSE	2.4900*	5.0248*	4.5384*	4.8011*	4.3499	5.2091*
Reuters	RMSE	41.924	30.103	5.0234*	14.809	29.392	10.727
	MAE	20.966*	17.707*	3.5876*	8.0467*	12.907*	7.7119
	MedAPE	0.9309	0.9132	0.9587*	0.8214*	0.9623*	0.7872
	MedSE	8.2482*	28.857*	6.8005*	9.9697*	9.6423*	10.999*
Rio Tinto	RMSE	10.869	6.0128	3.4454*	4.7250	4.5677	7.5312
	MAE	7.3027*	4.1183*	2.2865*	3.2169*	2.8857*	4.5662*
	MedAPE	0.9067*	0.8801	0.7433*	1.4147	0.8276*	0.9544*
	MedSE	4.6069*	4.5361*	2.0964*	3.8901*	2.2532*	4.1443*

Table 4.3 (continued). Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Royal & Sun Alliance Ins.	RMSE	43.625	25.855	22.719	5.4509*	15.861	10.559*
	MAE	23.410	13.942*	10.776*	3.4640*	8.9028	6.3775*
	MedAPE	0.8103*	0.8675*	0.8205*	1.2142	0.7068	3.0870
	MedSE	98.338	10.510*	6.1403*	6.9078	12.655*	9.3530
Royal Bank of Scotland	RMSE	20.920	17.104	18.537	13.564	16.051	9.0904
	MAE	11.814*	9.4253*	13.732	6.9486*	8.8060*	6.1095
	MedAPE	0.8324*	0.8465*	0.8840	0.9290*	2.1526	0.7237*
	MedSE	7.6545*	9.7041*	99.837	8.0264*	10.025*	12.159*
Sainsbury	RMSE	10.596	10.185	4.5058	6.6254	10.208	17.007
	MAE	4.6650*	4.5765*	3.0416*	3.6720*	4.2552*	5.6920*
	MedAPE	1.3687	0.8127*	0.7631	0.8976*	2.5742	0.9212*
	MedSE	2.7670*	2.6918*	2.7193*	3.7420*	3.4916*	2.8700
Scottish & Newcastle	RMSE	10.282	17.839	6.8990*	10.705	11.626	4.4383*
	MAE	4.9720	7.5154*	3.6825*	6.4976	7.7505	3.0393*
	MedAPE	0.6776	0.8548*	1.0842	0.8725	0.8662	0.8186*
	MedSE	3.4278*	4.6882*	4.5883*	5.2234*	7.0612*	4.6236*
Standard Chartered	RMSE	25.872	34.374	16.885	9.2925*	46.823	8.8239*
	MAE	16.261*	19.997*	10.406*	5.8064*	23.975*	5.4009*
	MedAPE	0.8780*	0.8779*	0.8034*	0.7543*	0.9686*	0.8397*
	MedSE	40.013*	16.121*	16.813*	14.612*	18.202*	11.745*
Unilever	RMSE	21.173	20.404	8.7553	6.4182	11.884	14.823
	MAE	12.040	9.0284*	4.0717*	3.8923*	7.3171	7.8149*
	MedAPE	0.7357*	0.7689*	0.8247*	0.8049	0.9370	0.8878*
	MedSE	9.6531*	1.6647*	1.9283*	1.5406	4.9652*	1.9460*

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 4.4. Forecast Error Statistics for the Random Walk Model

The random walk volatility forecast is expressed as:

$$h_{t+1} = s_t^2$$

where s_t^2 is the true volatility for period t.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
FTSE 100	RMSE	6.4250	7.8910	2.6481	4.3616	4.9386	1.8495
	MAE	4.9718	5.1121	1.9303	2.4929	3.5357	1.3460
	MedAPE	0.9808	0.9197	0.9796	0.9374	0.8181	0.9991*
	MedSE	15.094	2.6090	1.4462	0.5858	2.4529	0.7751
Asda	RMSE	9.9588	14.132	7.5551	10.377	7.9947	5.2039
	MAE	6.6551	10.482	5.2193	7.9423	5.8402	3.5596
	MedAPE	0.9812*	0.9807	0.8868	1.0531*	1.0000*	0.9131*
	MedSE	15.471*	54.454	14.336*	43.694	10.049*	4.9851*
Associated British Foods	RMSE	14.506	21.289	12.593	41.641	16.645	9.6761
	MAE	12.092	13.221	9.7201	29.846	11.990	6.0095
	MedAPE	0.9995	0.9626	0.9770	0.9673	0.9461	0.9489
	MedSE	116.57	21.214	47.662	261.05	121.69	14.349
BAA	RMSE	8.2329	5.0444	7.0444	8.2437	4.0324	9.8711
	MAE	5.5471	3.7073	5.5514	4.7319	2.8782	5.9512
	MedAPE	1.6329	0.9890	0.9390	0.9949*	1.4057*	1.0644*
	MedSE	4.1817	4.2867	22.423	2.0502*	3.3423	4.9521
BAT Industries	RMSE	327.28	13.983	13.954	11.701	64.731	5.3275
	MAE	113.73	10.293	8.4283	8.5217	33.438	4.3022
	MedAPE	0.9958	0.7992*	1.0119	0.8249	0.9961	0.7418
	MedSE	71.118	70.977	23.838	29.242	264.09	10.621
BOC	RMSE	7.2221	11.064	19.833	2.9780	5.2334	9.9233
	MAE	6.0796	7.9841	10.565	2.0195	3.7837	5.8633
	MedAPE	1.1408	0.9329	0.9841	0.9994*	0.9996*	0.9530
	MedSE	21.257	22.744	16.569	0.8009*	10.047	7.0408

Table 4.4 (continued). Forecast Error Statistics for the Random Walk Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
BG	RMSE	10.956	8.1818	3.6300	7.5287	18.538	8.9776
	MAE	6.4835	5.8130	2.3281	4.3931	10.588	5.5092
	MedAPE	0.8851*	0.9566	0.9869*	1.2222*	0.9861*	0.9109
	MedSE	7.5769	21.985	1.2679*	2.3438*	37.291	6.9229
BT	RMSE	11.289	12.708	14.221	6.8145	11.288	34.141
	MAE	7.4345	9.6105	10.649	4.9390	7.7700	15.934
	MedAPE	0.8741	0.9986	0.8961	0.8701	0.9448	2.3723
	MedSE	16.803	36.022	48.042	15.429	26.847	34.489
Barclays	RMSE	31.235	33.405	23.793	9.4672	16.401	15.095
	MAE	24.745	24.678	15.578	6.2562	11.624	11.596
	MedAPE	0.9931	0.9813	0.8726	0.9109	0.9827*	0.9917
	MedSE	579.22	194.93	45.464	7.0260	43.879	74.944
Bass	RMSE	47.274	20.160	28.742	10.473	26.278	13.800
	MAE	29.566	11.562	18.478	7.5141	15.065	8.0322
	MedAPE	0.9987	0.9949	1.3619	0.9643	0.9998	0.9744
	MedSE	504.73	30.626	28.002	27.877	28.490	7.1029
Blue Circle	RMSE	32.038	13.489	9.0359	5.4524	8.1765	12.999
	MAE	24.706	11.021	6.5286	3.7462	5.8600	9.6664
	MedAPE	0.9801	0.9934	1.3971	0.9606*	0.9994*	0.9233
	MedSE	355.39	159.03	19.749	2.5576	29.394	45.332
Boots	RMSE	5.5989	5.0943	25.580	6.3190	15.487	8.3735
	MAE	4.0395	3.9463	11.607	4.4525	9.2176	6.0218
	MedAPE	0.9113	0.9911	0.9980*	0.8313*	0.9893	0.9829*
	MedSE	9.0953	9.9043	2.1945*	4.6093	6.7191	10.447
British Airways	RMSE	23.726	19.387	14.904	11.808	10.228	8.5742
	MAE	17.549	13.930	9.9288	8.1349	7.4457	6.5404
	MedAPE	0.9345	0.8795	0.9128	0.9307	0.9996	0.9408
	MedSE	98.679	70.371	39.951	41.091	26.056	32.948

Table 4.4 (continued). Forecast Error Statistics for the Random Walk Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
CGU	RMSE	36.660	42.407	26.377	13.904	13.182	7.8510
	MAE	25.387	25.154	18.051	8.6211	10.452	6.0118
	MedAPE	0.9794	0.9554	0.9500	0.9524	0.9999	0.9417
	MedSE	299.12	118.97	226.50	10.504	71.444	23.287
Cadbury Schweppes	RMSE	10.244	22.091	2.7311	10.060	7.2691	8.3827
	MAE	6.9356	14.941	2.1087	6.7996	4.8592	5.3004
	MedAPE	1.8360	1.9507	0.8931	3.3980	0.9496*	0.9160*
	MedSE	16.775	40.229	1.7817*	13.541	7.3747	5.6960
Diageo	RMSE	42.520	27.255	17.035	20.729	12.655	9.1542
	MAE	30.769	17.208	10.255	14.901	7.4760	5.6027
	MedAPE	1.0022	0.9986	0.9085	0.9951	0.9799*	0.9371*
	MedSE	168.07	29.841	23.426	118.65	4.7474	5.7046
EMI	RMSE	90.833	14.294	68.299	5.5214	11.637	23.599
	MAE	45.069	9.8161	30.373	2.9737	8.1456	14.464
	MedAPE	0.9196*	0.9467*	1.1725	0.9000*	0.9945	0.9926
	MedSE	268.21	23.452	101.06	1.7864*	36.626	14.654
Enterprise Oil	RMSE	35.091	13.112	13.291	6.7716	14.695	8.0950
	MAE	24.552	9.0054	10.497	4.0749	7.7093	5.6489
	MedAPE	0.9424	0.9728	0.9793	0.9630*	1.0000	0.9475
	MedSE	274.47	47.732	64.195	1.8332*	11.460	10.449
General Electric	RMSE	31.634	14.798	9.7372	41.163	12.945	10.008
	MAE	18.770	9.9335	7.1017	22.402	9.1058	6.7099
	MedAPE	1.9658	0.9747	0.9749	0.9966	0.9440	2.1717
	MedSE	93.977	12.318	19.773	51.908	36.191	14.488
Glaxo Wellcome	RMSE	10.591	19.800	2.4215*	5.1830	7.6240	7.8906
	MAE	6.6540	11.346	1.1497*	3.4945	5.4812	5.0405
	MedAPE	0.9970	2.0111*	0.8664*	0.9650*	0.9984	0.9717
	MedSE	8.4879	12.501	0.1706*	3.3756*	10.831	7.1879

Table 4.4 (continued). Forecast Error Statistics for the Random Walk Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
ICI	RMSE	25.850	51.446	8.2666	11.327	20.336	21.717
	MAE	18.169	36.821	6.1746	8.0291	13.841	10.294
	MedAPE	0.9966	0.9853	0.9063	2.6411	1.2521	0.8494*
	MedSE	166.93	278.61	26.503	16.144	149.42	5.4169
Ladbroke	RMSE	36.863	18.064	28.941	12.130	21.101	71.535
	MAE	26.192	13.184	19.201	8.9884	13.925	29.311
	MedAPE	0.9147	0.9912	0.9907	0.9798	1.0000*	0.8855
	MedSE	336.30	71.628	82.346	38.630	102.62	41.537
Land Securities	RMSE	5.5833	4.8681	3.9406	2.3985	3.8128*	6.3741
	MAE	3.6958	3.6566	2.6067	1.5045	2.2093*	4.0412
	MedAPE	0.9795	1.1224*	0.9375	0.7703*	0.9259	0.9895*
	MedSE	2.7810	12.216	1.1427	0.4076*	1.3557*	6.4114
Legal & General	RMSE	41.908	46.077	14.077	13.085	24.694	15.065
	MAE	26.419	25.351	10.918	7.6193	12.316	11.143
	MedAPE	0.9859	0.7916*	0.9332	0.8856	0.9997	1.0714
	MedSE	17.142	45.100	116.78	18.038	20.314	27.799
Marks & Spencer	RMSE	16.157	9.9899	36.189	11.139	65.899	4.5508
	MAE	11.220	6.0865	18.245	7.0855	24.101	2.6178
	MedAPE	0.9689	0.9991	1.1225	0.9409	0.9850	0.9909*
	MedSE	19.960	12.306	63.750	19.522	17.224	0.1046*
Natwest Bank	RMSE	18.431	33.061	11.685	12.260	31.377	14.726
	MAE	12.731	22.789	8.0143	9.4252	19.020	9.8583
	MedAPE	0.8936	0.9376	0.8380	0.9822	0.9904	0.8954
	MedSE	54.711	135.55	46.619	49.233	79.981	25.235
Pearson	RMSE	18.948	11.474	5.5233	8.0266	10.019	11.300
	MAE	13.965	8.1450	3.9351	5.8982	6.4293	7.5884
	MedAPE	0.9663	0.9692	0.8834	0.9753	0.9994	0.8990*
	MedSE	169.11	53.284	5.4309	28.244	13.041	22.963

Table 4.4 (continued). Forecast Error Statistics for the Random Walk Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Prudential	RMSE	40.728	35.319	11.132	5.7163	12.459	11.386
	MAE	18.930	20.228	7.2075	3.9040	7.6914	9.0995
	MedAPE	0.8869	0.9850	0.9959	0.9036*	0.9880	0.9972
	MedSE	29.672	130.56	17.515	2.9269*	10.040	105.82
RMC	RMSE	44.214	22.147	6.6654	10.062	18.788	19.371
	MAE	25.307	14.279	4.1997	4.6383	10.902	10.954
	MedAPE	0.9469	1.1154	0.9912*	0.9235*	0.9983	1.1537
	MedSE	43.087	114.79	2.0083	0.6730*	25.238	4.9028
Rank Group	RMSE	29.595	22.746	21.349	19.319	21.393	34.963
	MAE	20.405	16.286	10.944	12.667	12.040	17.370
	MedAPE	0.9997	0.9729	0.8501	0.9915	0.9724	1.1406
	MedSE	170.82	208.73	17.336	95.138	27.900	35.621
Reckitt & Colman	RMSE	16.706	8.2567	75.481	3.5518	7.2674	23.670
	MAE	8.2368	5.6436	25.994	2.2016	5.3320	12.041
	MedAPE	0.9905	0.9053	0.9502*	0.9828*	0.9807	1.0944
	MedSE	1.7891	7.4976	2.1490	1.4343*	12.244	6.3422
Reed International	RMSE	15.351	10.694	7.9753	19.447	14.708	18.158
	MAE	10.032	7.3486	6.2245	11.232	8.1260	11.077
	MedAPE	0.9385	0.8154	0.9945	1.1587	0.9934*	0.8535*
	MedSE	21.230	7.2196	20.618	16.528	2.4649*	14.186
Reuters	RMSE	51.902	42.288	7.3541	16.516	38.629	8.3050
	MAE	28.604	31.078	5.5973	10.429	20.272	6.4230
	MedAPE	0.9835	0.9769	0.9827	0.8960	0.9985	0.5188
	MedSE	43.982	800.20	21.407	18.147	12.517	37.658
Rio Tinto	RMSE	13.837	7.9987	5.1332	6.9740	5.1564	9.6814
	MAE	10.199	5.4679	3.7575	5.1416	3.2774	6.6384
	MedAPE	0.9735	0.9794	0.9512	0.9741*	0.9985	1.3258
	MedSE	73.738	9.4534	5.3640	9.6058	4.6834	24.260

Table 4.4 (continued). Forecast Error Statistics for the Random Walk Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Royal & Sun Alliance Ins.	RMSE	56.253	29.550	32.450	7.4792	20.193	14.171
	MAE	34.750	17.852	19.021	4.3165	12.473	8.9089
	MedAPE	0.9052	0.9696	0.9049	0.9488*	0.9145	1.5424*
	MedSE	295.17	79.822	111.33	3.3644*	37.462	3.0889*
Royal Bank of Scotland	RMSE	23.044	21.714	17.487	17.232	21.219	12.250
	MAE	16.532	14.712	13.343	10.018	11.851	8.9677
	MedAPE	0.9884	1.6111	0.9688	0.9722	0.9877*	0.9817
	MedSE	251.47	47.796	112.55	16.670	10.656	52.341
Sainsbury	RMSE	13.623	14.975	6.4092	9.8791	15.092	23.576
	MAE	7.3586	8.5485	4.9964	6.3684	7.2459	9.2677
	MedAPE	0.9523*	0.9928	0.9875	0.9974	0.9996*	0.9971
	MedSE	12.919	9.1118	15.086	5.2103	5.0829	1.3866*
Scottish & Newcastle	RMSE	13.016	19.784	8.2279	13.359	15.125	5.6951
	MAE	7.4477	9.5876	4.6941	9.5164	11.263	4.0059
	MedAPE	0.7997	0.9675	0.9992*	0.9513	0.9996	0.9836
	MedSE	8.7339	6.7064	6.1873	48.440	73.171	7.1234
Standard Chartered	RMSE	34.585	37.547	21.028	11.914	65.640	12.323
	MAE	26.200	26.803	15.155	8.4195	40.525	8.1711
	MedAPE	0.9699	0.8896	0.9366	1.4064	0.9992	0.9673
	MedSE	373.67	416.48	119.80	31.927	478.96	18.981
Unilever	RMSE	23.781	26.710	9.8246	7.0761	14.606	16.589
	MAE	15.483	14.982	5.8537	5.2133	10.672	11.230
	MedAPE	0.8919	0.9305	0.9961	0.7988*	1.8301	0.9468
	MedSE	26.075	21.150	8.2861	11.917	89.506	46.524

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 4.5. Forecast Error Statistics for the Exponential smoothing Model

The exponential smoothing volatility forecast is expressed as:

$$h_{t+1} = \phi_T h_t + (1 - \phi_T) s_t^2$$

where ϕ is the smoothing parameter and s_t^2 is the true volatility.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
FTSE 100	RMSE	4.1200*	5.7316	2.4045	3.1995	3.4387*	1.6129
	MAE	3.4544	4.5057	2.2697	2.3012	2.2819	1.4294
	MedAPE	0.8268	2.1125	2.8573	3.3829	0.8024	4.0297
	MedSE	9.3954	15.820	5.2956	3.4767	1.6754	2.6361
Asda	RMSE	6.7483	10.160	5.3768	6.7993	5.4858	3.9582*
	MAE	5.4167	7.7092	4.7090	5.3674	4.7360	3.2953
	MedAPE	2.6223	0.8179	0.8515	2.6423	2.2207	2.0188
	MedSE	24.983	26.276	25.525	21.504	17.834	11.382
Associated British Foods	RMSE	9.3529	16.558*	10.315	28.364*	12.440	8.1063
	MAE	8.3942	10.946	8.9912	20.228	10.245	7.2856
	MedAPE	1.3538	1.2825	2.6406	0.8562*	2.2105	2.7504
	MedSE	81.066	56.665	98.848	190.84	115.16	59.278
BAA	RMSE	5.5573*	3.6388*	4.9927*	6.1774	2.8132	7.3798*
	MAE	4.1808	3.1052	3.8112	4.0326	2.5467	4.5281
	MedAPE	3.3916	0.7031*	0.9430	7.2236	7.1826	6.4053
	MedSE	9.0575	8.0340	7.7235	11.097	6.7508	8.6459
BAT Industries	RMSE	231.64*	11.957*	9.7157	8.7049*	45.725*	6.6664
	MAE	60.286	9.3179	7.2628	6.4611*	19.072	5.6892
	MedAPE	1.5329	1.4534	4.5056	0.6020*	0.9672	1.2378
	MedSE	72.044	56.221	58.281	27.759	73.303	34.779
BOC	RMSE	4.4094*	7.7432*	14.373*	4.1001	3.7014	8.5374*
	MAE	3.6712	5.3667	7.8542	3.9382	3.3784	4.9788
	MedAPE	0.6708*	0.6768*	5.9459	6.7489	4.8467	0.8589
	MedSE	13.230	19.524	31.588	17.624	12.033	10.264

Table 4.5 (continued). Forecast Error Statistics for the Exponential smoothing Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
BG	RMSE	10.076	6.4183	3.9728	5.0205	12.674*	7.2509
	MAE	7.6979	5.2328	3.6431	3.6622	6.5748	5.2178
	MedAPE	4.5923	1.6721	5.5616	15.390	2.4565	1.4409
	MedSE	41.185	29.913	13.321	10.251	10.799	19.551
BT	RMSE	7.4914*	10.323	10.179*	5.5567	8.6531	24.205*
	MAE	5.2716	7.8996	7.7670*	4.9737	6.3496	10.004
	MedAPE	0.8066	0.8089	0.7843*	3.1321	0.7944	3.7284
	MedSE	12.389	41.497	30.096	31.598	31.036	32.801
Barclays	RMSE	23.447*	22.554	16.870*	9.3065	11.346*	13.286*
	MAE	18.154	16.576	11.985	8.3605	8.5253	10.414
	MedAPE	1.1154	0.7845	0.9570	3.8206	3.1885	0.7780
	MedSE	170.57	164.02	88.101	73.694	55.394	67.662
Bass	RMSE	38.844	14.004	19.216*	8.9531	17.955*	11.383
	MAE	22.037	10.513	13.147	8.0805	10.272	9.1532
	MedAPE	1.5546	3.5843	1.5778	3.2342	1.6265	3.8830
	MedSE	224.27	102.79	85.214	78.483	42.352	64.393
Blue Circle	RMSE	20.841*	9.9180	6.9033	4.0324	7.3735	12.336
	MAE	17.142	9.1872	6.3131	3.6733	5.4259*	9.3130
	MedAPE	2.6110	1.6533	4.4017	4.2447	2.2685	0.7871*
	MedSE	267.92	123.04	43.099	13.036	10.256*	50.784
Boots	RMSE	3.6854	4.1123*	18.040*	4.8072	10.378*	6.3361*
	MAE	2.7099	3.5269	8.2103	4.2561	6.3264	5.2913
	MedAPE	0.8192	0.6848*	4.3319	2.2305	1.4208	3.9581
	MedSE	4.7984	12.023	19.027	14.349	15.365	21.203
British Airways	RMSE	19.405	14.114*	12.084	9.1275	8.8434	6.7588
	MAE	14.613	10.827	10.430	7.0602	6.8768	6.0304
	MedAPE	0.7904	0.6027	5.0823	1.9715	1.3023	1.0662
	MedSE	100.80	84.462	111.91	38.545	39.473	43.424

Table 4.5 (continued). Forecast Error Statistics for the Exponential smoothing Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
CGU	RMSE	27.542*	33.626	17.948*	11.180	8.4937*	5.7235
	MAE	18.929*	22.575	13.736	10.241	6.4513	4.5673
	MedAPE	0.8430	4.7707	2.1580	5.4984	0.7727	0.6564
	MedSE	193.18	382.35	156.85	92.797	26.680	15.517
Cadbury Schweppes	RMSE	6.9252*	14.966*	3.6954	7.7144	5.5000	6.8235
	MAE	4.3827	10.994	3.1893	5.3857	4.1728	4.5641
	MedAPE	1.1834	1.2089	3.6651	3.9848	3.4387	2.2600
	MedSE	8.4870	74.411	11.052	16.920	9.2950	10.069
Diageo	RMSE	29.398	18.202	11.597	14.718*	9.4580	8.2631
	MAE	17.677*	14.694	8.8414	11.791	8.1326	7.2746
	MedAPE	0.8908	3.8017	1.9624	1.2707	8.9970	3.9544
	MedSE	54.079	169.45	61.715	102.32	63.717	50.689
EMI	RMSE	63.662	13.679	53.084	11.364	9.0874	16.775*
	MAE	28.115	12.391	21.841	10.985	8.2145	12.133
	MedAPE	1.1693	4.3099	3.4006	18.838	5.1462	6.2028
	MedSE	198.79	149.94	110.65	135.00	80.784	82.914
Enterprise Oil	RMSE	26.753	9.0472	9.2816*	8.1219	10.999	6.5194
	MAE	18.667	8.2074	8.1706	7.7021	6.9540	5.4787
	MedAPE	1.0145	2.7059	0.6894	11.771	1.2901	1.1645
	MedSE	119.44	96.435	67.397	72.295	28.429	31.596
General Electric	RMSE	17.802	12.428	8.1985*	31.002*	9.2945	7.5592
	MAE	11.693	10.746	6.9270	18.019	7.2693	6.5617
	MedAPE	0.9096	7.5518	1.6540	3.9582	1.1998	3.7707
	MedSE	115.95	88.384	42.344	118.18	44.666	43.009
Glaxo Wellcome	RMSE	7.7208*	13.555	4.3296	3.9270	5.6956*	5.5371*
	MAE	5.6394	7.9879	4.0901	3.5647	4.3199	3.7400
	MedAPE	1.3129	5.6402	9.7183	3.0104	1.9159	0.6520*
	MedSE	21.419	27.956	20.898	14.228	13.719	11.783

Table 4.5 (continued). Forecast Error Statistics for the Exponential smoothing Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
ICI	RMSE	16.657*	37.208	10.365	9.1078	16.241*	16.839
	MAE	11.518	26.769	9.0032	8.9190	11.517	11.131
	MedAPE	1.1541	1.7454	3.1966	13.225	2.5541	2.9799
	MedSE	89.287	257.28	96.396	76.574	44.528	82.515
Ladbroke	RMSE	28.153	13.438	23.367	10.098	14.256*	51.121*
	MAE	17.135*	11.456	16.454	9.2499	10.606	21.423
	MedAPE	0.6551*	1.2371	1.9535	3.0218	5.5762	2.5046
	MedSE	114.87	137.00	139.98	94.801	74.006	127.50
Land Securities	RMSE	3.6894*	3.2806*	2.5205*	1.9628	4.1016	4.9823*
	MAE	2.5991	2.7602	1.9121	1.6992	2.8617	2.8981
	MedAPE	1.5834	2.2210	0.9304	1.6974	1.5083	6.1171
	MedSE	3.8409	5.3856	2.3012	2.6109	3.6691	4.8231
Legal & General	RMSE	34.238	31.661*	10.595	9.5405	17.267*	9.6388
	MAE	20.141	19.830	9.6917	7.7260	9.0666	8.1751
	MedAPE	3.3387	2.0161	1.7533	1.3030	1.9944	2.8414
	MedSE	82.021	135.77	121.56	58.068	40.156	54.250
Marks & Spencer	RMSE	11.492*	7.1608*	25.330*	9.6550	47.365*	7.0913
	MAE	7.2091	4.8172	11.844	6.6977	14.679	6.8731
	MedAPE	0.8939	1.5419	2.6322	4.2582	0.8074	23.515
	MedSE	19.786	16.113	45.346	38.998	17.045	54.019
Natwest Bank	RMSE	14.649*	21.718*	11.170	8.4268	20.502*	13.330*
	MAE	9.4324	15.603	8.5484	6.9967	11.179	9.3983
	MedAPE	0.8317	2.1084	1.4625	1.0968	1.2464	0.8593
	MedSE	48.629	106.30	76.507	54.582	45.484	58.327
Pearson	RMSE	18.469*	7.4540	5.1872	6.2537	6.8433	7.7555*
	MAE	11.772	6.5507	4.7101	5.3140	4.8042	6.0234
	MedAPE	0.7788*	1.3998	1.4687	2.5689	2.2269	4.3065
	MedSE	51.916	43.631	25.279	28.887	20.697	19.866

Table 4.5 (continued). Forecast Error Statistics for the Exponential smoothing Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Prudential	RMSE	33.036	28.696	8.9015	5.7970	9.0183	8.3495*
	MAE	13.120*	18.725	7.8275	5.0874	5.7054	6.4220
	MedAPE	0.8672	2.0882	2.9814	3.2873	1.7140	0.7736
	MedSE	12.948	190.48	53.030	19.369	11.797	19.593
RMC	RMSE	34.326	14.322	8.6608	8.1713	15.594	14.208
	MAE	20.421	11.432	8.2077	6.9326	9.1125	9.6435
	MedAPE	1.8746	4.4121	19.173	14.171	0.8594*	3.9382
	MedSE	144.84	131.49	78.391	46.598	33.970	49.850
Rank Group	RMSE	20.844*	15.544*	19.309*	10.353	14.080*	23.869*
	MAE	13.755	12.957	11.194	9.4662	9.0505	11.871
	MedAPE	0.8415	3.0327	1.8978	3.1812	1.3549	1.7038
	MedSE	88.062	128.12	64.723	99.147	57.515	47.741
Reckitt & Colman	RMSE	13.870	5.6703*	52.809*	4.8195	5.9411*	16.672*
	MAE	8.2536	4.0923	16.866	4.5303	4.8330	8.4858
	MedAPE	4.6766	0.8872	5.8927	15.150	1.8955	2.9664
	MedSE	20.396	11.491	30.737	26.909	19.112	26.569
Reed International	RMSE	10.624*	7.3212*	5.7812	13.864*	9.9716	14.964
	MAE	7.7913	5.9278	5.0529	8.4501	7.6398	9.5668
	MedAPE	1.9167	1.0318	0.9394	2.4516	9.1235	2.7206
	MedSE	30.547	28.525	23.498	35.109	33.652	40.174
Reuters	RMSE	39.139*	26.073*	11.475	13.733	28.283*	8.9079
	MAE	24.424	20.293	10.679	10.041	15.367	7.7759
	MedAPE	1.5469	1.0789	7.1917	1.7568	3.0536	0.7618
	MedSE	172.86	270.69	101.02	63.388	69.439	38.763
Rio Tinto	RMSE	9.5377*	5.9949	3.7845	4.6925	4.5373	7.2710*
	MAE	8.2750	4.8764	3.1855	3.5874	3.1667	5.1356
	MedAPE	2.2055	1.3800	1.7297	2.2072	1.0466	3.3590
	MedSE	54.259	28.734	10.379	8.4093	7.3690	10.559

Table 4.5 (continued). Forecast Error Statistics for the Exponential smoothing Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Royal & Sun Alliance Ins.	RMSE	40.785	23.228	21.023*	9.8270	14.298	10.904
	MAE	22.203	17.219	13.951	9.6538	8.3432	9.1283
	MedAPE	0.8394	1.6856	1.9154	7.7999	0.6575	9.6374
	MedSE	84.334*	149.76	127.56	101.68	31.488	66.835
Royal Bank of Scotland	RMSE	18.649	15.591	14.708*	13.458	15.319	8.2266
	MAE	12.450	11.685	10.796	10.997	10.860	6.3202
	MedAPE	1.0674	1.3083	0.5509*	3.6488	8.2370	0.7693
	MedSE	56.836	119.29	127.73	111.48	75.282	41.235
Sainsbury	RMSE	10.288*	9.7989*	4.1292*	6.3433*	10.039*	16.724*
	MAE	4.9228	4.8864	3.3192	4.3970	5.2636	6.4768
	MedAPE	2.4245	0.8818	0.7009	1.5505	6.1093	2.5751
	MedSE	10.417	8.2730	10.217	14.621	13.516	10.024
Scottish & Newcastle	RMSE	9.9760	17.505*	6.7319	10.066*	10.640	4.6452
	MAE	4.8193*	7.8241	4.2492	6.4427*	7.6893*	3.8722
	MedAPE	0.6483*	0.9731	2.5498	0.8217*	0.8629*	1.9049
	MedSE	5.6123	9.7063	9.9835	13.066	15.669	16.225
Standard Chartered	RMSE	22.055*	29.912	15.415	10.991	44.069*	12.555
	MAE	16.875	23.032	12.705	9.5602	24.788	11.723
	MedAPE	1.0894	1.7843	1.6605	2.8335	3.1544	4.5588
	MedSE	258.59	362.48	208.23	114.65	173.06	160.89
Unilever	RMSE	19.197	18.915	8.4093	5.7511	10.566*	13.408*
	MAE	11.743	13.128	5.6997	4.5506	7.4745	8.6201
	MedAPE	0.8978	3.2241	2.6150	1.3701	0.8255*	3.1140
	MedSE	52.289	85.230	21.048	14.435	21.177	36.404

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 4.6. Best Forecast Model for the GARCH Type Models							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Asda	RMSE	GJR	GJR	ACGARCH	GJR	ACGARCH	ACGARCH
	MAE	ACGARCH	GJR	ACGARCH	GJR	ACGARCH	ACGARCH
	MedAPE	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH
	MedSE	ACGARCH	GJR	ACGARCH	GJR	ACGARCH	ACGARCH
Associated British Foods	RMSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MAE	GJR	GJR	GJR	ACGARCH	ACGARCH	ACGARCH
	MedAPE	GJR	GJR	GJR	ACGARCH	ACGARCH	ACGARCH
	MedSE	ACGARCH	GJR	GJR	GJR	ACGARCH	ACGARCH
BAA	RMSE	ACGARCH	GJR	GJR	ACGARCH	ACGARCH	GJR
	MAE	ACGARCH	GJR	GJR	ACGARCH	ACGARCH	ACGARCH
	MedAPE	ACGARCH	GJR	GJR	ACGARCH	GJR	ACGARCH
	MedSE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
BG	RMSE	ACGARCH	ACGARCH	GJR	GJR	GJR	ACGARCH
	MAE	ACGARCH	GJR	GJR	GJR	GJR	ACGARCH
	MedAPE	GJR	GJR	GJR	GJR	GJR	ACGARCH
	MedSE	ACGARCH	GJR	GJR	GJR	GJR	GJR
BT	RMSE	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH	ACGARCH
	MAE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedAPE	ACGARCH	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH
Barclays	RMSE	GJR	ACGARCH	GJR	GJR	GJR	GJR
	MAE	GJR	ACGARCH	GJR	GJR	GJR	ACGARCH
	MedAPE	GJR	ACGARCH	ACGARCH	ACGARCH	GJR	GJR
	MedSE	GJR	ACGARCH	ACGARCH	GJR	GJR	GJR
Bass	RMSE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MAE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedAPE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedSE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH

Table 4.6 (continued). Best Forecast Model for the GARCH Type Models							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Blue Circle	RMSE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MAE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR
	MedAPE	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH	GJR
	MedSE	ACGARCH	ACGARCH	ACGARCH	GJR	GJR	GJR
Boots	RMSE	GJR	GJR	GJR	ACGARCH	ACGARCH	GJR
	MAE	ACGARCH	GJR	GJR	ACGARCH	GJR	GJR
	MedAPE	ACGARCH	GJR	GJR	GJR	ACGARCH	ACGARCH
	MedSE	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH	ACGARCH
British Airways	RMSE	GJR	GJR	ACGARCH	ACGARCH	GJR	GJR
	MAE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR	GJR
	MedAPE	GJR	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedSE	GJR	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH
CGU	RMSE	GJR	ACGARCH	ACGARCH	GJR	ACGARCH	GJR
	MAE	ACGARCH	ACGARCH	ACGARCH	GJR	GJR	GJR
	MedAPE	GJR	ACGARCH	ACGARCH	GJR	ACGARCH	GJR
	MedSE	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH	GJR
Cadbury Schweppes	RMSE	GJR	GJR	GJR	ACGARCH	ACGARCH	ACGARCH
	MAE	GJR	GJR	GJR	GJR	ACGARCH	ACGARCH
	MedAPE	ACGARCH	GJR	GJR	ACGARCH	ACGARCH	ACGARCH
	MedSE	ACGARCH	ACGARCH	GJR	GJR	ACGARCH	ACGARCH
Diageo	RMSE	GJR	GJR	GJR	GJR	GJR	ACGARCH
	MAE	GJR	ACGARCH	GJR	GJR	GJR	ACGARCH
	MedAPE	ACGARCH	ACGARCH	ACGARCH	GJR	GJR	GJR
	MedSE	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH	ACGARCH
EMI	RMSE	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH	ACGARCH
	MAE	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH	GJR
	MedAPE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedSE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR

Table 4.6 (continued). Best Forecast Model for the GARCH Type Models

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Enterprise Oil	RMSE	ACGARCH	ACGARCH	GJR	ACGARCH	GJR	ACGARCH
	MAE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedAPE	ACGARCH	ACGARCH	GJR	ACGARCH	GJR	ACGARCH
	MedSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
General Electric	RMSE	GJR	GJR	GJR	GJR	ACGARCH	GJR
	MAE	GJR	ACGARCH	GJR	GJR	ACGARCH	GJR
	MedAPE	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH	GJR
	MedSE	ACGARCH	ACGARCH	GJR	ACGARCH	GJR	GJR
Glaxo Wellcome	RMSE	ACGARCH	ACGARCH	GJR	GJR	ACGARCH	ACGARCH
	MAE	GJR	ACGARCH	GJR	GJR	GJR	ACGARCH
	MedAPE	GJR	ACGARCH	GJR	GJR	GJR	ACGARCH
	MedSE	GJR	ACGARCH	GJR	GJR	GJR	GJR
ICI	RMSE	GJR	GJR	ACGARCH	GJR	ACGARCH	ACGARCH
	MAE	GJR	ACGARCH	ACGARCH	GJR	GJR	ACGARCH
	MedAPE	ACGARCH	ACGARCH	ACGARCH	GJR	GJR	ACGARCH
	MedSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Ladbroke	RMSE	ACGARCH	GJR	GJR	GJR	ACGARCH	GJR
	MAE	ACGARCH	ACGARCH	GJR	GJR	GJR	GJR
	MedAPE	GJR	ACGARCH	ACGARCH	GJR	GJR	GJR
	MedSE	GJR	ACGARCH	GJR	GJR	ACGARCH	GJR
Land Securities	RMSE	GJR	GJR	GJR	GJR	ACGARCH	GJR
	MAE	ACGARCH	GJR	GJR	GJR	GJR	ACGARCH
	MedAPE	ACGARCH	GJR	GJR	GJR	GJR	GJR
	MedSE	ACGARCH	ACGARCH	GJR	GJR	GJR	ACGARCH
Legal & General	RMSE	GJR	GJR	ACGARCH	ACGARCH	GJR	ACGARCH
	MAE	ACGARCH	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedAPE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH

Table 4.6 (continued). Best Forecast Model for the GARCH Type Models							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Marks & Spencer	RMSE	GJR	ACGARCH	ACGARCH	GJR	ACGARCH	GJR
	MAE	GJR	ACGARCH	ACGARCH	GJR	ACGARCH	GJR
	MedAPE	GJR	GJR	ACGARCH	ACGARCH	GJR	GJR
	MedSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR
Pearson	RMSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR
	MAE	ACGARCH	ACGARCH	GJR	GJR	GJR	GJR
	MedAPE	ACGARCH	ACGARCH	GJR	GJR	GJR	GJR
	MedSE	ACGARCH	GJR	ACGARCH	GJR	GJR	GJR
Prudential	RMSE	ACGARCH	GJR	GJR	GJR	ACGARCH	GJR
	MAE	GJR	ACGARCH	GJR	GJR	GJR	GJR
	MedAPE	GJR	ACGARCH	GJR	GJR	GJR	GJR
	MedSE	ACGARCH	ACGARCH	GJR	GJR	GJR	ACGARCH
RMC	RMSE	ACGARCH	GJR	GJR	GJR	ACGARCH	ACGARCH
	MAE	GJR	GJR	GJR	GJR	ACGARCH	GJR
	MedAPE	GJR	GJR	GJR	GJR	ACGARCH	ACGARCH
	MedSE	GJR	ACGARCH	GJR	GJR	GJR	GJR
Rank Group	RMSE	GJR	GJR	ACGARCH	ACGARCH	GJR	GJR
	MAE	GJR	ACGARCH	GJR	ACGARCH	GJR	GJR
	MedAPE	GJR	GJR	GJR	ACGARCH	GJR	GJR
	MedSE	GJR	ACGARCH	GJR	ACGARCH	GJR	ACGARCH
Reed International	RMSE	ACGARCH	GJR	GJR	ACGARCH	GJR	ACGARCH
	MAE	GJR	GJR	GJR	GJR	GJR	GJR
	MedAPE	GJR	GJR	ACGARCH	ACGARCH	GJR	GJR
	MedSE	GJR	GJR	ACGARCH	GJR	GJR	GJR
Reuters	RMSE	GJR	GJR	GJR	ACGARCH	ACGARCH	ACGARCH
	MAE	GJR	GJR	GJR	GJR	GJR	GJR
	MedAPE	GJR	ACGARCH	GJR	GJR	GJR	ACGARCH
	MedSE	GJR	GJR	GJR	GJR	GJR	GJR

Table 4.6 (continued). Best Forecast Model for the GARCH Type Models

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Rio Tinto	RMSE	ACGARCH	GJR	ACGARCH	ACGARCH	GJR	ACGARCH
	MAE	GJR	GJR	ACGARCH	GJR	GJR	GJR
	MedAPE	GJR	GJR	ACGARCH	ACGARCH	ACGARCH	GJR
	MedSE	GJR	ACGARCH	ACGARCH	GJR	GJR	GJR
Royal & Sun Alliance Ins.	RMSE	ACGARCH	GJR	ACGARCH	ACGARCH	GJR	ACGARCH
	MAE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedAPE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
	MedSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Royal Bank of Scotland	RMSE	GJR	ACGARCH	GJR	ACGARCH	GJR	GJR
	MAE	GJR	ACGARCH	GJR	ACGARCH	ACGARCH	GJR
	MedAPE	GJR	ACGARCH	GJR	ACGARCH	GJR	GJR
	MedSE	GJR	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR
Sainsbury	RMSE	ACGARCH	GJR	GJR	GJR	GJR	ACGARCH
	MAE	ACGARCH	GJR	GJR	GJR	GJR	ACGARCH
	MedAPE	GJR	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH
	MedSE	GJR	ACGARCH	GJR	ACGARCH	ACGARCH	ACGARCH
Standard Chartered	RMSE	GJR	ACGARCH	ACGARCH	GJR	GJR	ACGARCH
	MAE	GJR	ACGARCH	ACGARCH	GJR	GJR	ACGARCH
	MedAPE	ACGARCH	ACGARCH	GJR	GJR	GJR	ACGARCH
	MedSE	ACGARCH	ACGARCH	ACGARCH	GJR	GJR	ACGARCH
Unilever	RMSE	ACGARCH	GJR	ACGARCH	GJR	ACGARCH	GJR
	MAE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR	GJR
	MedAPE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR
	MedSE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. GJR and ACGARCH denote the GARCH/GJR and CGARCH/ACGARCH models respectively.

Table 4.7. Best Forecast Model Overall							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
FTSE 100	RMSE	ES	GJR	GJR	GJR	ES	HM
	MAE	GJR	HM	HM	HM	GJR	HM
	MedAPE	GJR	HM	HM	HM	HM	RW
	MedSE	HM	HM	HM	HM	HM	HM
Asda	RMSE	HM	GJR	HM	HM	HM	ES
	MAE	HM	HM	HM	HM	ACGARCH	ACGARCH
	MedAPE	RW	HM	ACGARCH	RW	RW	RW
	MedSE	RW	HM	RW	GJR	RW	RW
Associated British Foods	RMSE	ACGARCH	ES	ACGARCH	ES	ACGARCH	HM
	MAE	HM	GJR	GJR	HM	HM	HM
	MedAPE	GJR	HM	HM	ES	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
BAA	RMSE	ES	ES	ES	ACGARCH	HM	ES
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	HM	ES	GJR	RW	RW	RW
	MedSE	HM	HM	HM	RW	HM	HM
BAT Industries	RMSE	ES	ES	HM	ES	ES	HM
	MAE	HM	HM	HM	ES	HM	HM
	MedAPE	HM	RW	HM	ES	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
BOC	RMSE	ES	ES	ES	HM	GJR	ES
	MAE	HM	GJR	HM	HM	HM	HM
	MedAPE	ES	ES	HM	RW	RW	HM
	MedSE	HM	HM	HM	RW	HM	HM
BG	RMSE	ACGARCH	ACGARCH	HM	HM	ES	ACGARCH
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	RW	HM	RW	RW	RW	HM
	MedSE	HM	HM	RW	RW	HM	HM

Table 4.7 (continued). Best Forecast Model Overall							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
BT	RMSE	ES	ACGARCH	ES	ACGARCH	ACGARCH	ES
	MAE	HM	ACGARCH	ES	HM	ACGARCH	HM
	MedAPE	HM	GJR	ES	HM	ACGARCH	HM
	MedSE	HM	HM	HM	HM	HM	HM
Barclays	RMSE	ES	ACGARCH	ES	HM	ES	ES
	MAE	HM	ACGARCH	GJR	HM	HM	HM
	MedAPE	HM	ACGARCH	ACGARCH	HM	RW	GJR
	MedSE	HM	HM	HM	HM	HM	HM
Bass	RMSE	GJR	ACGARCH	ES	ACGARCH	ES	ACGARCH
	MAE	GJR	HM	HM	HM	HM	HM
	MedAPE	HM	HM	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Blue Circle	RMSE	ES	ACGARCH	HM	HM	ACGARCH	ACGARCH
	MAE	ACGARCH	HM	HM	HM	ES	GJR
	MedAPE	HM	HM	HM	RW	RW	ES
	MedSE	HM	HM	HM	HM	ES	HM
Boots	RMSE	GJR	ES	ES	ACGARCH	ES	ES
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	HM	ES	RW	RW	HM	RW
	MedSE	HM	HM	RW	HM	HM	HM
British Airways	RMSE	GJR	ES	ACGARCH	ACGARCH	GJR	GJR
	MAE	ACGARCH	ACGARCH	HM	HM	HM	HM
	MedAPE	GJR	GJR	HM	HM	HM	ACGARCH
	MedSE	HM	ACGARCH	HM	HM	HM	HM
CGU	RMSE	ES	ACGARCH	ES	GJR	ES	GJR
	MAE	ES	HM	HM	HM	GJR	HM
	MedAPE	GJR	HM	HM	HM	ACGARCH	GJR
	MedSE	HM	HM	HM	HM	HM	HM

Table 4.7 (continued). Best Forecast Model Overall							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Cadbury Schweppes	RMSE	ES	ES	HM	ACGARCH	ACGARCH	ACGARCH
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	ACGARCH	GJR	HM	HM	RW	RW
	MedSE	HM	HM	RW	HM	HM	HM
Diageo	RMSE	GJR	GJR	GJR	ES	HM	ACGARCH
	MAE	ES	HM	HM	HM	HM	HM
	MedAPE	HM	HM	HM	HM	RW	RW
	MedSE	HM	HM	HM	HM	HM	HM
EMI	RMSE	ACGARCH	HM	GJR	HM	HM	ES
	MAE	ACGARCH	HM	HM	HM	HM	HM
	MedAPE	RW	RW	HM	RW	HM	HM
	MedSE	HM	HM	HM	RW	HM	HM
Enterprise Oil	RMSE	ACGARCH	HM	ES	ACGARCH	GJR	ACGARCH
	MAE	HM	HM	HM	ACGARCH	HM	HM
	MedAPE	HM	HM	GJR	RW	HM	HM
	MedSE	HM	HM	HM	RW	ACGARCH	HM
General Electric	RMSE	GJR	GJR	ES	ES	ACGARCH	HM
	MAE	HM	HM	HM	HM	ACGARCH	HM
	MedAPE	ACGARCH	HM	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Glaxo Wellcome	RMSE	ES	ACGARCH	RW	HM	ES	ES
	MAE	HM	HM	RW	HM	HM	HM
	MedAPE	HM	RW	RW	RW	HM	ES
	MedSE	HM	HM	RW	RW	HM	HM
ICI	RMSE	ES	GJR	ACGARCH	GJR	ES	ACGARCH
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	ACGARCH	HM	HM	HM	HM	RW
	MedSE	HM	HM	HM	HM	HM	HM

Table 4.7 (continued). Best Forecast Model Overall							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Ladbroke	RMSE	ACGARCH	GJR	GJR	GJR	ES	ES
	MAE	ES	HM	HM	HM	HM	HM
	MedAPE	ES	HM	HM	HM	RW	HM
	MedSE	GJR	HM	HM	HM	HM	HM
Land Securities	RMSE	ES	ES	ES	HM	RW	ES
	MAE	HM	HM	HM	HM	RW	HM
	MedAPE	HM	RW	HM	RW	HM	RW
	MedSE	HM	HM	HM	RW	RW	HM
Legal & General	RMSE	GJR	ES	ACGARCH	ACGARCH	ES	ACGARCH
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	HM	RW	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Marks & Spencer	RMSE	ES	ES	ES	GJR	ES	HM
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	GJR	HM	HM	HM	HM	RW
	MedSE	HM	HM	HM	HM	HM	RW
Natwest Bank	RMSE	ES	ES	GJR	GJR	ES	ES
	MAE	GJR	HM	HM	HM	HM	HM
	MedAPE	GJR	HM	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Pearson	RMSE	ES	ACGARCH	ACGARCH	ACGARCH	ACGARCH	ES
	MAE	ACGARCH	HM	HM	HM	HM	HM
	MedAPE	ES	HM	GJR	HM	HM	RW
	MedSE	HM	HM	HM	HM	HM	HM
Prudential	RMSE	ACGARCH	GJR	GJR	HM	ACGARCH	ES
	MAE	ES	ACGARCH	HM	HM	HM	GJR
	MedAPE	HM	ACGARCH	HM	RW	HM	GJR
	MedSE	HM	HM	HM	RW	HM	HM

Table 4.7 (continued). Best Forecast Model Overall

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
RMC	RMSE	ACGARCH	GJR	HM	HM	ACGARCH	ACGARCH
	MAE	GJR	HM	HM	HM	ACGARCH	HM
	MedAPE	HM	HM	RW	RW	ES	HM
	MedSE	HM	HM	HM	RW	HM	HM
Rank Group	RMSE	ES	ES	ES	ACGARCH	ES	ES
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	GJR	HM	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Reckitt & Colman	RMSE	GJR	ES	ES	HM	ES	ES
	MAE	HM	GJR	HM	HM	GJR	HM
	MedAPE	HM	GJR	RW	RW	GJR	HM
	MedSE	HM	HM	HM	RW	HM	HM
Reed International	RMSE	ES	ES	GJR	ES	HM	ACGARCH
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	HM	HM	HM	HM	RW	RW
	MedSE	HM	HM	HM	HM	RW	HM
Reuters	RMSE	ES	ES	HM	ACGARCH	ES	ACGARCH
	MAE	HM	HM	HM	HM	HM	GJR
	MedAPE	GJR	ACGARCH	HM	HM	HM	ACGARCH
	MedSE	HM	HM	HM	HM	HM	HM
Rio Tinto	RMSE	ES	GJR	HM	ACGARCH	GJR	ES
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	HM	GJR	HM	RW	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Royal & Sun Alliance Ins.	RMSE	ACGARCH	GJR	ES	HM	GJR	HM
	MAE	ACGARCH	HM	HM	HM	ACGARCH	HM
	MedAPE	HM	HM	HM	RW	ACGARCH	RW
	MedSE	ES	HM	HM	RW	HM	RW

Table 4.7 (continued). Best Forecast Model Overall							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Royal Bank of Scotland	RMSE	GJR	ACGARCH	ES	ACGARCH	GJR	GJR
	MAE	HM	HM	GJR	HM	HM	GJR
	MedAPE	HM	HM	ES	HM	RW	HM
	MedSE	HM	HM	ACGARCH	HM	HM	HM
Sainsbury	RMSE	ES	ES	ES	ES	ES	ES
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	RW	HM	ACGARCH	HM	RW	HM
	MedSE	HM	HM	HM	HM	HM	RW
Scottish & Newcastle	RMSE	GJR	ES	HM	ES	GJR	HM
	MAE	ES	HM	HM	ES	ES	HM
	MedAPE	ES	HM	RW	ES	ES	HM
	MedSE	HM	HM	HM	HM	HM	HM
Standard Chartered	RMSE	ES	ACGARCH	ACGARCH	HM	ES	HM
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	HM	HM	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Unilever	RMSE	ACGARCH	GJR	ACGARCH	GJR	ES	ES
	MAE	ACGARCH	HM	HM	HM	GJR	HM
	MedAPE	HM	HM	HM	RW	ES	HM
	MedSE	HM	HM	HM	HM	HM	HM

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. GJR, ACGARCH, HM, RW and ES denote the GARCH/GJR, CGARCH/ACGARCH, historical mean, random walk and exponential smoothing models respectively.

Table 4.8. Forecast Error Statistics for the GARCH /GJR Model (Monthly Data)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise and $M_t = 1$ when the day of the week is Monday and zero otherwise. The GJR model reduces down to the GARCH model when $\gamma_1 = 0$.

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	49.302	44.425	1.2450	2,133.4
Asda	45.324*	37.574	0.3920	1,348.5
Associated British Foods	220.30	197.89	0.8976	29,356
BAA	39.001	33.466	0.4761*	1,448.8
BAT Industries	520.21	356.88	0.7977	7,1695
BOC	43.401*	36.999	0.3294	1,177.0
BG	59.928	49.905	0.5797	3,400.2
BT	117.77	111.16	0.7805	16,529
Barclays	319.47	270.65	0.8599	67,913
Bass	201.79	165.73	0.7023	21,427
Blue Circle	133.82	105.78	0.6393	7,809.3
Boots	74.287	64.418*	0.6413	2,632.1
British Airways	97.134*	67.146*	0.2540*	1,437.8*
CGU	178.35*	132.02*	0.5875*	9,786.0*
Cadbury Schweppes	79.228	54.085	0.5034	2,041.7
Diageo	198.29	157.81	0.7418	18,736
EMI	245.18*	179.68	0.7019	16,886
Enterprise Oil	115.74*	92.848*	0.4481*	10,605
General Electric	159.70	145.59	0.8578	16,565
Glaxo Wellcome	56.282	51.097	0.5849	2,358.8
ICI	149.13*	113.60*	0.2219*	7,258.4
Ladbroke	198.79	174.22	0.6639	30,512
Land Securities	18.028*	15.598*	0.3225*	274.29*

Table 4.8 (continued). Forecast Error Statistics for the GARCH /GJR Model (Monthly Data)				
Stock/Index	**RMSE**	**MAE**	**MedAPE**	**MedSE**
Legal & General	217.86	189.39	0.8443	15,594
Marks & Spencer	138.53*	112.20*	0.7255*	9,435.5*
Natwest Bank	136.95*	109.75*	0.5448*	17,498*
Pearson	112.55	87.716*	0.6390	4,099.1*
Prudential	165.26	135.81	0.6995	9,410.5
RMC	191.00	163.15	0.7849	23,195
Rank Group	128.37	96.620	0.4364	11,768
Reckitt & Colman	117.76*	103.66	0.8509	9,769.8
Reed International	76.653	68.169*	0.4421*	2,812.2*
Reuters	245.63	205.50	0.6733	40,362
Rio Tinto	61.862	51.284	0.5381	2,033.4
Royal & Sun Alliance Ins.	249.90	199.65	0.8028	37,879
Royal Bank of Scotland	170.10	147.99	0.6627	11,984*
Sainsbury	60.234	56.189	0.6229	3,524.8
Scottish & Newcastle	115.37	108.24	0.8839	14,425
Standard Chartered	390.18	328.56	1.1803	102,508
Unilever	142.47*	124.28	0.7889	16,139

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 4.9. Forecast Error Statistics for the CGARCH/ACGARCH Model (Monthly Data)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t$$
$$h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$
$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	80.849	66.884	0.9192	2,962.8
Asda	50.934	40.134	0.4353	1,567.5
Associated British Foods	223.05	200.72	0.9193	32,124
BAA	35.692	32.482	0.4910	1,424.4
BAT Industries	498.06*	313.44*	0.7211*	53,825
BOC	50.916	48.118	0.5137	2,406.9
BG	61.008	53.615	0.6238	4,687.8
Blue Circle	129.36	99.286	0.6340	4,437.2
Boots	79.350	68.685	0.5321*	1,936.7*
EMI	268.57	197.73	0.7431	9869.7
Enterprise Oil	151.83	116.71	0.7169	11,089
General Electric	148.50*	137.21	0.8051	16,297
ICI	198.77	174.30	0.6814	27,884
Ladbroke	186.22*	155.73*	0.5275*	22,047*
Land Securities	22.341	20.297	0.4385	535.69
Legal & General	188.26*	152.10*	0.6799	7,621.9*
Natwest Bank	148.71	136.29	0.6333	17,662
Pearson	115.16	89.393	0.6742	4,581.9
RMC	200.19	150.87	0.6396	7,742.0*
Rank Group	91.402*	71.877*	0.3092*	2,659.3*
Reed International	75.178*	70.575	0.4960	3,844.9
Reuters	241.34	203.96	0.8400	38,898
Rio Tinto	63.316	52.723	0.5162	1,985.2

Table 4.9 (continued). Forecast Error Statistics for the CGARCH/ACGARCH Model (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
Standard Chartered	527.55	399.32	0.7669	212,944
Unilever	142.86	121.10*	0.6836*	12,179*

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 4.10. Forecast Error Statistics for the Historical Mean Model (Monthly Data)

The historical mean volatility forecast is expressed as:

$$h_{t+1} = \bar{s}_t^2 = \frac{1}{t}\sum_{j=1}^{t} s_j^2$$

where s_t^2 is the true volatility.

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	39.990*	32.215*	0.5838*	808.87*
Asda	47.063	44.294	0.3825	1,426.8
Associated British Foods	214.84	191.75	0.8646	27,246
BAA	36.499	33.030	0.5238	1,331.2
BAT Industries	500.65	317.80	0.7509	21,118*
BOC	69.094	58.733	0.6401	3,960.1
BG	58.314	48.630	0.5620	3,191.1
BT	119.43	113.25	0.7853	15,008
Barclays	216.07*	183.95*	0.7002*	28,898*
Bass	198.13	171.55	0.7896	19,683
Blue Circle	120.37	92.820	0.5637	7,808.6
Boots	73.994*	69.063	0.6524	3,441.0
British Airways	152.27	119.72	0.4280	3,615.5
CGU	227.45	190.22	0.7457	27,355
Cadbury Schweppes	76.659	55.993	0.4869*	1,855.4
Diageo	193.76	160.12	0.7771	20,923
EMI	275.28	197.84	0.7107	14,025
Enterprise Oil	151.13	101.72	0.4501	2,796.8*
General Electric	154.83	139.57	0.7940	14,279
Glaxo Wellcome	48.410*	40.229*	0.5061	1,574.4*
ICI	214.14	168.57	0.6917	19,750
Ladbroke	237.08	213.90	0.7623	42,163
Land Securities	21.649	19.413	0.4494	515.94
Legal & General	199.56	167.06	0.6610*	11,957
Marks & Spencer	145.96	118.74	0.7549	11,392

Table 4.10 (continued). Forecast Error Statistics for the Historical Mean Model (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
Natwest Bank	163.60	155.21	0.7281	25,978
Pearson	114.10	94.262	0.6595	4,496.2
Prudential	164.85	135.08	0.6931	9,186.3
RMC	158.29*	112.79*	0.5664*	9,057.3
Rank Group	158.77	148.18	0.6879	21,948
Reckitt & Colman	119.31	94.880*	0.7253	6,686.6*
Reed International	89.469	84.990	0.6509	7,869.1
Reuters	224.89	184.59	0.6495	24,398
Rio Tinto	60.002	49.664	0.4875	1,790.4
Royal & Sun Alliance Ins.	240.02	190.83	0.7597*	32,463
Royal Bank of Scotland	154.11*	140.77*	0.6299*	15,749
Sainsbury	58.211	56.223	0.5884	3,016.1
Scottish & Newcastle	97.473	88.797	0.7345	10,045
Standard Chartered	243.85*	194.45*	0.6437*	46,117
Unilever	144.65	130.83	0.7969	16,595

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 4.11. Forecast Error Statistics for the Random Walk Model (Monthly Data)

The random walk volatility forecast is expressed as:

$$h_{t+1} = s_t^2$$

where s_t^2 is the true volatility for period t.

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	122.08	86.898	0.9567	2,809.0
Asda	85.271	75.187	0.8305	7,130.3
Associated British Foods	216.36	190.00	0.8633	25,702*
BAA	64.591	58.420	0.8756	3,800.5
BAT Industries	615.03	431.55	0.7381	80,846
BOC	97.958	69.941	0.5261	1,904.5
BG	70.809	61.759	0.6849	5,805.6
BT	113.65	109.84	0.7922	13,185
Barclays	707.65	487.24	0.7813	36,640
Bass	239.73	210.36	0.9231	39,116
Blue Circle	196.91	157.92	0.9679	20,944
Boots	167.36	115.70	0.8240	5,019.8
British Airways	686.60	452.13	0.6796	26,415
CGU	290.18	216.35	0.8333	18,161
Cadbury Schweppes	212.50	139.81	0.9998	8,103.5
Diageo	220.09	173.64	0.7752	28,286
EMI	407.53	295.87	0.8369	35,677
Enterprise Oil	326.71	288.97	1.0859	101,748
General Electric	152.46	118.67*	0.7091*	6,320.6*
Glaxo Wellcome	126.92	105.13	0.8450	6,637.2
ICI	313.56	239.20	0.9325	27,992
Ladbroke	186.81	171.63	0.6666	24,818
Land Securities	30.658	24.480	0.4712	628.12
Legal & General	412.87	323.02	0.9480	79,176
Marks & Spencer	221.47	201.38	0.9807	42,140
Natwest Bank	441.76	325.78	0.8735	37,116

Table 4.11 (continued). Forecast Error Statistics for the Random Walk Model (Monthly Data)				
Stock/Index	**RMSE**	**MAE**	**MedAPE**	**MedSE**
Pearson	110.18*	99.509	0.6361*	7,115.7
Prudential	135.47*	115.19	0.7615	8,733.6
RMC	363.87	279.06	0.8581	72,474
Rank Group	308.62	237.41	1.3242	41,208
Reckitt & Colman	187.04	140.62	0.5150*	13,626
Reed International	109.49	108.03	0.8501	11,860
Reuters	574.89	428.80	0.8545	84,162
Rio Tinto	72.942	66.839	0.7641	3,275.4
Royal & Sun Alliance Ins.	209.39*	183.02*	0.7811	30,059*
Royal Bank of Scotland	703.86	448.91	0.7953	16,826
Sainsbury	56.810*	55.181*	0.6186	2,528.6*
Scottish & Newcastle	85.070*	83.232*	0.6661*	6,491.5*
Standard Chartered	1055.2	683.41	0.9607	136,502
Unilever	261.58	211.21	0.9352	33,655

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 4.12. Forecast Error Statistics for the Exponential Smoothing Model (Monthly Data)

The exponential smoothing volatility forecast is expressed as:

$$h_{t+1} = \phi_T h_t + (1 - \phi_T) s_t^2$$

where ϕ is the smoothing parameter and s_t^2 is the true volatility.

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	88.602	63.518	1.1356	2,255.8
Asda	46.783	34.796*	0.2636*	677.19*
Associated British Foods	212.14*	188.71*	0.8481*	26,216
BAA	34.220*	31.463*	0.5081	1,254.0*
BAT Industries	498.54	317.83	0.7560	21,369
BOC	44.698	36.502*	0.3138*	1,121.0*
BG	48.299*	42.607*	0.5071*	1,895.4*
BT	95.520*	87.630*	0.6189*	9,355.4*
Barclays	738.62	584.52	2.0149	194,668
Bass	170.67*	117.76*	0.3444*	3,716.6*
Blue Circle	116.87*	86.827*	0.5289*	3,815.0*
Boots	77.597	72.963	0.7008	3,640.6
British Airways	571.33	476.49	1.9631	131,218
CGU	298.53	232.59	0.8007	24,536
Cadbury Schweppes	76.620*	51.988*	0.5186	1,004.1*
Diageo	176.00*	122.35*	0.3750*	5,975.3*
EMI	251.90	162.35*	0.5475*	5,479.5*
Enterprise Oil	169.85	137.11	0.7452	14,923
General Electric	155.06	139.91	0.7968	14,389
Glaxo Wellcome	49.856	41.613	0.4943*	1,756.9
ICI	205.74	151.22	0.3753	5,299.3*
Ladbroke	234.75	211.58	0.7530	41,295
Land Securities	21.997	19.763	0.4586	541.33
Legal & General	357.53	253.42	0.8451	52,594
Marks & Spencer	146.48	119.48	0.7690	12,001
Natwest Bank	347.50	232.93	0.5975	23,327

Table 4.12 (continued). Forecast Error Statistics for the Exponential Smoothing Model (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
Pearson	113.78	94.334	0.6680	4,616.2
Prudential	142.51	101.60*	0.4786*	3,325.6*
RMC	159.89	129.60	0.7196	8,929.8
Rank Group	195.16	167.65	0.7512	31,238
Reckitt & Colman	132.48	108.44	0.7408	8,678.1
Reed International	79.026	73.768	0.5170	4,951.3
Reuters	222.01*	173.73*	0.6172*	22,138*
Rio Tinto	59.310*	48.612*	0.4775*	1,701.0*
Royal & Sun Alliance Ins.	240.48	192.17	0.7688	33,224
Royal Bank of Scotland	428.37	317.65	1.0381	44,926
Sainsbury	57.769	55.852	0.5877*	2,996.9
Scottish & Newcastle	111.11	103.66	0.8562	13,538
Standard Chartered	320.71	253.53	1.1722	42,087*
Unilever	184.64	147.41	0.7289	12,823

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 4.13. Best Forecast Model for the GARCH Type Models (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	GJR	GJR	ACGARCH	GJR
Asda	GJR	GJR	GJR	GJR
Associated British Foods	GJR	GJR	GJR	GJR
BAA	ACGARCH	ACGARCH	GJR	ACGARCH
BAT Industries	ACGARCH	ACGARCH	ACGARCH	ACGARCH
BOC	GJR	GJR	GJR	GJR
BG	GJR	GJR	GJR	GJR
Blue Circle	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Boots	GJR	GJR	ACGARCH	ACGARCH
EMI	GJR	GJR	GJR	ACGARCH
Enterprise Oil	GJR	GJR	GJR	GJR
General Electric	ACGARCH	ACGARCH	ACGARCH	ACGARCH
ICI	GJR	GJR	GJR	GJR
Ladbroke	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Land Securities	GJR	GJR	GJR	GJR
Legal & General	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Natwest Bank	GJR	GJR	GJR	GJR
Pearson	GJR	GJR	GJR	GJR
RMC	GJR	ACGARCH	ACGARCH	ACGARCH
Rank Group	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Reed International	ACGARCH	GJR	GJR	GJR
Reuters	ACGARCH	ACGARCH	GJR	ACGARCH
Rio Tinto	GJR	GJR	ACGARCH	ACGARCH
Standard Chartered	GJR	GJR	ACGARCH	GJR
Unilever	GJR	ACGARCH	ACGARCH	ACGARCH

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. GJR and ACGARCH denote the GARCH/GJR and CGARCH/ACGARCH models respectively.

Table 4.14. Best Forecast Model Overall (Monthly Data)				
Stock/Index	**RMSE**	**MAE**	**MedAPE**	**MedSE**
FTSE 100	HM	HM	HM	HM
Asda	GJR	ES	ES	ES
Associated British Foods	ES	ES	ES	RW
BAA	ES	ES	GJR	ES
BAT Industries	ACGARCH	ACGARCH	ACGARCH	HM
BOC	GJR	ES	ES	ES
BG	ES	ES	ES	ES
BT	ES	ES	ES	ES
Barclays	HM	HM	HM	HM
Bass	ES	ES	ES	ES
Blue Circle	ES	ES	ES	ES
Boots	HM	GJR	ACGARCH	ACGARCH
British Airways	GJR	GJR	GJR	GJR
CGU	GJR	GJR	GJR	GJR
Cadbury Schweppes	ES	ES	HM	ES
Diageo	ES	ES	ES	ES
EMI	GJR	ES	ES	ES
Enterprise Oil	GJR	GJR	GJR	HM
General Electric	ACGARCH	RW	RW	RW
Glaxo Wellcome	HM	HM	ES	HM
ICI	GJR	GJR	GJR	ES
Ladbroke	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Land Securities	GJR	GJR	GJR	GJR
Legal & General	ACGARCH	ACGARCH	HM	ACGARCH
Marks & Spencer	GJR	GJR	GJR	GJR
Natwest Bank	GJR	GJR	GJR	GJR
Pearson	RW	GJR	RW	GJR
Prudential	RW	ES	ES	ES
RMC	HM	HM	HM	ACGARCH

Table 4.14 (continued). Best Forecast Model Overall (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
Rank Group	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Reckitt & Colman	GJR	HM	RW	HM
Reed International	ACGARCH	GJR	GJR	GJR
Reuters	ES	ES	ES	ES
Rio Tinto	ES	ES	ES	ES
Royal & Sun Alliance Ins.	RW	RW	HM	RW
Royal Bank of Scotland	HM	HM	HM	GJR
Sainsbury	RW	RW	ES	RW
Scottish & Newcastle	RW	RW	RW	RW
Standard Chartered	HM	HM	HM	ES
Unilever	GJR	ACGARCH	ACGARCH	ACGARCH

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. GJR, ACGARCH, HM, RW and ES denote the GARCH/GJR, CGARCH/ACGARCH, historical mean, random walk and exponential smoothing models respectively.

Appendix 3

Table 4.15. Forecast Error Statistics for the GARCH/GJR Model (Rolling Equation Estimation)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise and $M_t = 1$ when the day of the week is Monday and zero otherwise. The GJR model reduces down to the GARCH model when $\gamma_1 = 0$.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
FTSE 100	RMSE	4.1378	5.5274	2.2198	3.1952	3.5412	1.4509
	MAE	3.3936	3.8824	1.952	2.0471	2.183	1.2639
	MedAPE	0.7721	1.292	1.6544	2.4054	0.7727	3.0894
	MedSE	7.19	8.9189	3.0601	2.1881	0.8861	2.0499
Asda	RMSE	6.9326*	10.029*	5.7744	6.8703*	5.6507	4.0782
	MAE	5.7724	7.8696*	5.1606	5.4858*	4.8375	3.4598
	MedAPE	3.4002	0.9974	1.0446	2.6063*	2.0165	1.7656*
	MedSE	29.99	36.193*	25.253	18.532*	20.388	10.093
Associated British Foods	RMSE	9.1993	16.661	9.8186	29.354	12.918	9.4213
	MAE	7.8163*	10.108*	8.4451*	21.107	10.614	8.6187
	MedAPE	0.7568*	0.8696*	1.8654*	0.9562*	2.3512*	3.1561*
	MedSE	48.088	23.116*	56.505*	156.96*	124.5	94.275
BAA	RMSE	5.7392	3.7773*	5.1187*	6.1238	2.7462	7.4249*
	MAE	4.1564	2.9587*	4.0284*	3.5889	2.2692	4.3975
	MedAPE	4.015	0.7799*	0.8202*	4.9098	5.6634*	4.9505*
	MedSE	5.8352*	5.284	7.6373	5.9844	4.5396	5.2130*
BAT Industries	RMSE	234.39	15.225	10.893	9.0015	46.144	7.6277
	MAE	83.169	13.56	9.1366	6.4501	20.471	6.387
	MedAPE	9.4896	2.6295	5.9894	0.6526	1.737	1.4744
	MedSE	1162.4	237.68	76.99	21.825	98.384	48.99

Table 4.15 (continued). Forecast Error Statistics for the GARCH/GJR Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
BOC	RMSE	4.4582	7.8917	14.343	3.4088	3.6238	8.7269
	MAE	3.6378	5.3417	7.4818	3.1917	3.0015	4.973
	MedAPE	0.7045	0.7103	5.3497	5.0388	3.4163	0.8795
	MedSE	12.279	15.29	26.275	12.84	6.1688	6.5489
BG	RMSE	10.258*	6.2368*	3.0920*	4.9960*	12.817*	7.3411
	MAE	7.3149	4.6862*	2.5265*	3.3158*	6.7366*	5.2089
	MedAPE	3.2179	0.9590*	3.0305*	13.366*	2.1336*	1.2358
	MedSE	31.733	18.632	4.6491*	6.4455*	10.439*	18.233
BT	RMSE	7.8067	10.27	10.633*	4.7117*	8.6683*	24.511
	MAE	5.2358	7.5625	7.9139*	4.3213*	6.0097*	9.9608
	MedAPE	0.849	0.7608*	0.8283	2.5457*	0.7982*	2.8947
	MedSE	11.044	29.442	26.394	22.515	16.590*	21.196
Barclays	RMSE	23.568*	22.038	16.975*	8.1570*	11.491	13.521*
	MAE	17.882	15.423	10.531*	6.6932*	8.2126*	10.09
	MedAPE	1.0177*	0.7562	0.776	2.3733	2.4323*	0.7773*
	MedSE	143.44*	136.11	46.171	37.126*	33.244*	49.803*
Bass	RMSE	38.030*	13.63	19.782	8.2599	18.225*	11.118
	MAE	18.960*	9.1545	12.991	7.167	10.778	8.6557
	MedAPE	0.9237*	2.2228	1.0378	2.6157	2.0128	3.9683
	MedSE	58.256*	49.833	63.215	51.365	48.664	58.946
Blue Circle	RMSE	20.894*	9.5989	6.6254*	4.1707*	7.1615	12.13
	MAE	16.609	8.8126	5.9860*	3.8215*	5.4204	8.1889*
	MedAPE	1.8416	1.2695	4.4401	4.0487*	2.2300*	0.8102*
	MedSE	240.47	80.849	39.453	13.815	16.086*	23.291*
Boots	RMSE	3.6753*	4.1058*	18.121*	4.7850*	10.524	6.4124*
	MAE	2.7436	3.5099	8.4066*	4.1731*	6.2475*	5.2378
	MedAPE	0.8767	0.6874*	4.3362*	2.1789*	1.2459	3.5636
	MedSE	4.8069	11.509	21.744	13.418	12.391	19.001*

Table 4.15 (continued). Forecast Error Statistics for the GARCH/GJR Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
British Airways	RMSE	18.980*	14.153*	11.339	9.0792	8.5191*	6.6564*
	MAE	14.724*	10.471	9.1869	6.8558	6.3314	6.0114*
	MedAPE	0.7846*	0.5898*	4.3375	1.8352	1.1839*	1.1175
	MedSE	130.49*	61.453	77.115	32.123	34.904	38.22
CGU	RMSE	28.084*	32.998	18.129	10.417*	8.7366	5.5865*
	MAE	19.271	20.147	13.295	8.9428*	6.3861*	4.3365*
	MedAPE	0.7774*	3.7457	1.491	4.0641*	0.8158	0.5970*
	MedSE	153.55	183.04	97.915	67.371*	28.354*	20.221
Cadbury Schweppes	RMSE	6.9871*	15.005*	2.5266*	7.681	5.4946	6.9053
	MAE	4.1667*	10.386*	2.3469*	4.8760*	3.901	4.2229*
	MedAPE	0.9154	0.8879*	2.0946*	2.7957	2.7138	1.47
	MedSE	7.423	48.642	4.7428*	9.0030*	4.9505	5.6154*
Diageo	RMSE	28.405*	17.524*	11.204	15.032*	8.5442*	8.2818
	MAE	18.136*	13.221	7.4009*	11.434*	6.5708*	6.4978
	MedAPE	1.1021	2.6607	1.1248*	1.0378*	6.0919*	2.6389*
	MedSE	97.8	115.48	33.822*	75.747	32.682	27.925
EMI	RMSE	63.6	13.89	52.721*	10.132	8.2794	17.001*
	MAE	28.291	12.574	21.641*	9.7555	7.0571	10.993*
	MedAPE	1.1258*	4.7157	3.8085	16.126	4.3339	4.5157*
	MedSE	167.29*	173.02	131.22	110.35	52.857	41.513*
Enterprise Oil	RMSE	26.399	9.4975	9.4364*	5.7357*	10.912	6.6005*
	MAE	22.339	8.171	8.3089*	4.7036	5.2546*	5.2719*
	MedAPE	3.2989	1.9858	0.5984*	6.6899	0.7475*	1.177
	MedSE	408.34	68.869	74.67	14.759	6.2977*	19.983
General Electric	RMSE	17.592*	11.642*	8.2867*	31.271*	9.3448	6.9250*
	MAE	10.378*	8.9513*	5.9329*	17.237*	6.618	5.1053*
	MedAPE	0.7477	4.7569	1.0008	2.9985*	0.8324	2.4078*
	MedSE	87.205	51.956	20.275*	78.345	23.750*	17.101*

Table 4.15 (continued). Forecast Error Statistics for the GARCH/GJR Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Glaxo Wellcome	RMSE	7.879	13.623*	3.0616*	3.4676*	5.9272	5.6936
	MAE	5.1474*	8.6629*	2.4919*	2.6925*	4.1031*	3.8795*
	MedAPE	0.8886*	6.6938*	5.0834*	1.3042*	1.2791*	0.7317*
	MedSE	12.051*	32.337	5.4600*	6.3046*	6.9313*	11.528*
ICI	RMSE	16.815*	37.029	8.7486	7.8872*	16.721	16.736
	MAE	11.575*	25.996*	7.5423*	7.3556*	11.259*	10.749
	MedAPE	1.0459	1.534	2.5532	9.4073*	2.2327*	2.9883*
	MedSE	77.48	222.2	79.23	51.356*	47.706*	66.192
Ladbroke	RMSE	27.961	13.001*	22.931*	9.4037*	14.701	51.239*
	MAE	17.915	10.556	14.817*	8.5210*	10.555*	18.593*
	MedAPE	0.7875*	1.0338*	1.4524	2.2345*	4.5850*	1.0661*
	MedSE	107.22*	93.649	80.332*	69.113*	56.297	29.802*
Land Securities	RMSE	3.7203*	3.3344*	2.5665	1.8959	4.2161	5.0623
	MAE	2.726	2.7746*	1.7569*	1.5012	2.7665	2.9271
	MedAPE	2.0094	2.0692*	0.7451	1.2375	1.4447*	6.4305*
	MedSE	3.9061	5.3887	1.5508*	1.6211*	2.8996	4.4635*
Legal & General	RMSE	34.111*	32.062*	10.078	9.1548*	17.264*	9.8237
	MAE	19.484	18.373	9.0334	6.9984	9.1117	8.2275
	MedAPE	2.6104	1.4675	1.4091	1.0116*	1.8635	3.0438
	MedSE	55.464	132.55	95.774	35.498	43.035	47.017
Marks & Spencer	RMSE	11.697*	7.1598*	25.678*	9.4476*	47.809	6.2258*
	MAE	7.4041	4.7332	12.233	6.2112	15.55	6.0423
	MedAPE	0.8427*	1.2117	2.3863	3.8003	1.0388	20.231
	MedSE	17.424	11.345	40.064	27.283	19.976	35.845
Natwest Bank	RMSE	14.903	21.85	10.996	8.346	20.896	13.581
	MAE	9.3847	15.722	7.7656	6.3227	11.168	9.0322
	MedAPE	0.7911	2.0442	1.1062	1.0255	1.4528	0.8325
	MedSE	52.982	128.2	51.94	34.842	27.255	41.743

Table 4.15 (continued). Forecast Error Statistics for the GARCH/GJR Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Pearson	RMSE	19.069	6.6951	4.6903	6.1775	6.8373	7.8255*
	MAE	11.758	5.352	3.9899*	4.8138*	4.2841*	5.7968*
	MedAPE	0.8153	0.8869	0.7635*	1.6336*	1.3585*	3.6382*
	MedSE	35.267	20.305*	14.041	14.223*	10.253*	14.057*
Prudential	RMSE	32.72	26.780*	8.0704*	5.5339	9.0143	8.5418
	MAE	13.238*	14.483	5.4209*	4.2430*	5.2606*	5.9545
	MedAPE	0.9201*	0.8401	1.1682*	2.7185*	1.2877	0.6696*
	MedSE	16.798	73.417	14.907*	11.499*	6.8485*	15.281*
RMC	RMSE	34.283	14.220*	6.8235*	7.4395*	15.485	14.368*
	MAE	19.199*	10.949*	6.4985*	5.1609*	9.0714*	8.8849*
	MedAPE	1.6731*	3.8034*	14.579*	10.199*	1.3438	4.2195*
	MedSE	110.26	96.748	40.808*	19.874*	32.611*	29.784*
Rank Group	RMSE	21.628*	16.133*	19.523	9.9584	14.363*	24.367*
	MAE	13.732*	12.597	9.2895*	8.547	7.6791*	11.255*
	MedAPE	0.8056*	2.0367*	0.8551*	2.189	1.0454*	0.9915*
	MedSE	74.415*	93.464	20.664*	79.313	24.056	31.288
Reckitt & Colman	RMSE	13.628	5.7987	53.843	3.7526	6.0713	16.81
	MAE	7.3331	3.7754	17.859	3.3234	4.302	8.3661
	MedAPE	4.6833	0.7066	4.7186	10.517	0.8458	2.4
	MedSE	13.627	6.2012	13.876	9.2158	7.9106	18.92
Reed International	RMSE	10.800*	7.4317*	5.7353*	14.069*	10.072*	14.821
	MAE	7.6478*	5.6342*	4.8661*	7.9623	6.6980*	8.7738*
	MedAPE	1.5126*	0.8347*	0.7832	2.2795	6.7301*	1.3583*
	MedSE	21.606*	23.091*	23.528	22.326	16.448*	17.312*
Reuters	RMSE	39.580*	27.863*	6.5707*	13.366	29.177	8.2061
	MAE	21.689*	20.212*	5.8151*	8.6032*	14.039*	6.0416*
	MedAPE	0.9216*	0.9616	3.5540*	0.9499*	1.1543*	0.5547
	MedSE	56.239*	186.10*	30.754*	24.422*	12.946*	19.248*
Rio Tinto	RMSE	9.7075*	5.5914*	3.6533	4.6845*	4.4350*	7.3804
	MAE	7.6148*	4.3846*	2.9791	3.5378	3.0344*	4.8471*
	MedAPE	1.4703*	0.8218*	1.3651	2.516	1.0753	2.6384*
	MedSE	25.019*	17.320*	9.5527	8.4887	5.2754*	8.6586*

Table 4.15 (continued). Forecast Error Statistics for the GARCH/GJR Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Royal & Sun Alliance Ins.	RMSE	40.426*	23.227*	21.053	10.24	14.191*	11.023
	MAE	21.942*	17.324	14.183	10.023	8.6195	9.442
	MedAPE	0.8275*	1.7438	2.0955	8.2688	0.6324*	10.378
	MedSE	99.527*	153.66	144.73	110.36	37.642	76.437
Royal Bank of Scotland	RMSE	18.629*	15.566	14.868*	12.883	15.241*	8.1481*
	MAE	12.279*	10.524	10.643*	9.7552	10.426*	6.0823*
	MedAPE	0.9457	0.9729	0.6073*	3.6513	7.8508*	0.7682*
	MedSE	56.787*	66.543	75.682	83.434	57.400*	29.085*
Sainsbury	RMSE	10.451	9.9130*	4.2082*	6.4190*	10.147*	16.951
	MAE	5.1974	5.0550*	3.5102*	4.3584*	5.1501*	6.2661
	MedAPE	2.2038*	0.9542	0.7078	1.4896	4.8972*	2.3852
	MedSE	10.789*	7.8464	9.9285*	12.258*	11.42	6.9702
Scottish & Newcastle	RMSE	9.476	17.855	6.996	10.18	10.298	5.3161
	MAE	5.8299	9.8594	5.017	7.5328	7.9735	4.4153
	MedAPE	1.2582	3.5058	3.992	0.9661	0.9381	3.4696
	MedSE	15.748	36.919	14.956	38.096	59.166	16.989
Standard Chartered	RMSE	22.275	29.531	14.799*	9.5547*	44.316*	11.71
	MAE	17.330*	22.603	11.563	7.5318*	24.549*	10.582
	MedAPE	1.1718	1.5263	1.2047*	1.6296*	2.8703*	4.3136
	MedSE	255.99	316.89	115.31	38.095*	158.94*	108.23
Unilever	RMSE	19.204	18.832*	8.4201	5.5574*	10.688	13.482*
	MAE	11.039	11.567	5.7201	4.4015*	7.1599*	8.2795*
	MedAPE	0.8253*	2.6469	2.6429	1.3650*	0.8543	2.2970*
	MedSE	25.058	56.643	23.4	15.022*	16.150*	23.319*

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 4.16. Forecast Error Statistics for the CGARCH/ACGARCH Model (Rolling Equation Estimation)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \; h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$
$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Asda	RMSE	7.0329	10.361	5.4376*	7.041	5.6003*	4.0164*
	MAE	5.3937*	7.8872	4.5690*	5.6677	4.7152*	3.2646*
	MedAPE	2.7154*	0.8453*	0.6603*	3.0818	1.8740*	1.6483
	MedSE	19.230*	38.076	17.498*	23.84	16.926*	9.0696*
Associated British Foods	RMSE	9.1879*	16.577*	9.7961*	29.090*	12.458*	7.8927*
	MAE	7.8934	10.305	8.64	20.935*	10.099*	6.9810*
	MedAPE	0.8322	0.9438	1.9457	0.9599	2.0981	2.485
	MedSE	44.596*	28.424	72.49	177.91	86.236*	50.277*
BAA	RMSE	5.7327*	3.8317	5.1475	6.0713*	2.7254*	7.431
	MAE	4.0934*	3.0167	4.0522	3.5132*	2.2571*	4.3594*
	MedAPE	3.7998*	0.7952	0.834	4.6427*	5.9266	5.0548
	MedSE	6.1819	5.1847*	7.4114*	5.3152*	4.2260*	5.2346
BG	RMSE	10.298	6.3425	3.2371	5.1553	12.825	7.2865*
	MAE	7.1873*	4.7696	2.8188	3.6975	6.9956	5.1681*
	MedAPE	2.8871*	1.0342	3.6454	15.665	2.8456	1.2206*
	MedSE	28.031*	16.005*	7.1197	9.5236	15.233	17.343*
BT	RMSE	7.7898*	10.267*	10.639	4.7301	8.713	24.495*
	MAE	5.2234*	7.5218*	7.9174	4.326	6.0425	9.9517*
	MedAPE	0.8462*	0.7614	0.8275*	2.5659	0.8029	2.7584*
	MedSE	10.940*	29.058*	25.908*	22.009*	16.691	20.984*
Barclays	RMSE	23.598	21.970*	17.127	8.3847	11.268*	13.543
	MAE	17.734*	15.334*	10.867	7.0502	8.4037	10.067*
	MedAPE	1.1126	0.6022*	0.7614*	2.2516*	2.5687	0.7811
	MedSE	175.52	135.04*	41.342*	41.006	46.862	50.891

Table 4.16 (continued). Forecast Error Statistics for the CGARCH/ACGARCH Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Bass	RMSE	38.227	13.581*	19.767*	8.0050*	18.278	10.920*
	MAE	19.008	9.0616*	12.584*	6.7468*	10.382*	8.1697*
	MedAPE	1.0155	2.0981*	0.9486*	2.2690*	1.6972*	3.3650*
	MedSE	73.676	46.325*	55.769*	40.469*	37.580*	46.424*
Blue Circle	RMSE	21.011	9.4151*	6.6536	4.1999	7.1459*	12.105*
	MAE	16.016*	8.6855*	6.0544	3.8381	5.3699*	8.3785
	MedAPE	1.4754*	1.1358*	4.1370*	4.2806	2.3466	0.8155
	MedSE	172.57*	78.182*	35.661*	13.416*	16.386	24.898
Boots	RMSE	3.7161	4.2055	18.387	4.8127	10.495*	6.4694
	MAE	2.6307*	3.5084*	8.8194	4.1812	6.2497	5.2040*
	MedAPE	0.7233*	0.7039	4.6981	2.3912	1.2278*	3.4068*
	MedSE	3.9617*	7.8183*	18.745*	12.625*	11.088*	19.07
British Airways	RMSE	19.903	14.772	11.030*	8.8698*	8.6891	6.8238
	MAE	15.351	10.322*	8.4467*	6.6001*	6.3298*	6.1074
	MedAPE	0.8594	0.5942	3.4698*	1.3478*	1.3989	0.7815*
	MedSE	140.36	53.345*	57.023*	32.030*	27.825*	35.506
CGU	RMSE	28.493	32.002*	18.084*	10.736	8.4229*	5.7678
	MAE	19.090*	18.778*	12.897*	9.369	6.4176	4.643
	MedAPE	0.8158*	2.7481*	1.1980*	4.6013	0.7569*	0.6269
	MedSE	114.10*	148.10*	86.966*	76.201	31.447	19.196*
Cadbury Schweppes	RMSE	7.0616	15.413	2.798	7.5447*	5.4545*	6.7297*
	MAE	4.2558	10.456	2.5771	4.985	3.7239*	4.3201
	MedAPE	0.8885*	0.9621	2.4289	2.4616*	2.2974*	1.4667*
	MedSE	6.8917*	42.919*	6.3446	9.1273	4.5694*	7.6426
Diageo	RMSE	29.464	18.004	11.096*	15.039	8.6621	7.9035*
	MAE	18.199	13.084*	7.4564	11.58	6.7214	6.2508*
	MedAPE	1.0083*	2.5477*	1.1303	1.2561	6.4873	2.9483
	MedSE	72.513*	97.510*	35.762	73.816*	30.227*	23.071*

Table 4.16 (continued). Forecast Error Statistics for the CGARCH/ACGARCH Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
EMI	RMSE	63.326*	12.367*	53.631	9.8722*	7.9036*	17.007
	MAE	28.012*	10.708*	22.137	9.3995*	6.4764*	11.445
	MedAPE	1.308	3.0158*	2.3793*	14.271*	3.7756*	5.304
	MedSE	182.65	99.172*	75.164*	79.673*	42.029*	49.68
Enterprise Oil	RMSE	25.548*	8.1128*	10.393	5.8366	10.886*	6.6958
	MAE	19.285*	6.9565*	9.055	4.2167*	5.3677	5.2968
	MedAPE	1.7457*	1.2266*	0.6954	5.9177*	0.8862	1.0774*
	MedSE	259.42*	45.479*	74.415*	3.9302*	8.4859	18.754*
General Electric	RMSE	17.625	11.733	8.3699	31.997	9.1594*	6.9319
	MAE	10.872	8.972	6.0427	18.071	6.5490*	5.1325
	MedAPE	0.7211*	4.3907*	0.8717*	3.3847	0.7831*	2.6639
	MedSE	78.880*	50.272*	25.837	71.494*	24.537	18.151
Glaxo Wellcome	RMSE	7.8455*	13.689	3.1047	3.5609	5.8321*	5.6742*
	MAE	5.1914	8.814	2.5746	2.9615	4.1868	3.8983
	MedAPE	0.9134	6.9018	6.4907	1.8393	1.3877	0.743
	MedSE	13.058	30.874*	7.7534	7.8509	9.8393	13.138
ICI	RMSE	17.063	37.009*	8.1483*	8.1569	16.498*	16.618*
	MAE	11.635	25.214	7.104	7.6749	11.443	9.8069*
	MedAPE	0.8625*	1.2596*	2.2010*	10.188	2.9792	2.5918
	MedSE	70.349*	192.23*	69.555*	54.783	38.76	45.215*
Ladbroke	RMSE	27.831*	13.085	23.853	9.7743	14.575*	51.837
	MAE	17.700*	10.504*	16.055	8.7957	10.836	22.549
	MedAPE	0.8442	1.0472	1.1870*	2.753	6.1014	2.132
	MedSE	134.56	76.082*	102.11	77.024	55.815*	74.564
Land Securities	RMSE	3.7401	3.3365	2.5603*	1.8930*	4.1595*	5.0536*
	MAE	2.6695*	2.7751	1.7671	1.4996*	2.7493*	2.9238*
	MedAPE	1.9809*	2.2561	0.7285*	1.1843*	1.5555	6.4551
	MedSE	3.6340*	4.9831*	1.612	1.6664	2.7251*	4.4701

Table 4.16 (continued). Forecast Error Statistics for the CGARCH/ACGARCH Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Legal & General	RMSE	34.14	32.177	9.8379*	9.2219	17.308	9.7595*
	MAE	19.194*	18.246*	8.7213*	6.9092*	9.0540*	8.0803*
	MedAPE	2.3209*	1.2185*	1.2246*	1.0589	1.7437*	2.8241*
	MedSE	52.977*	104.83*	88.338*	33.711*	43.819	45.732*
Marks & Spencer	RMSE	11.738	7.1938	25.712*	9.4524	47.795*	6.2729
	MAE	7.3844*	4.7303*	12.231*	6.2106*	15.442*	6.0585
	MedAPE	0.8489	1.1176*	2.2894*	3.7212*	1.0334*	19.924*
	MedSE	16.093*	10.945*	38.589*	26.773*	19.566*	33.987*
Pearson	RMSE	18.913*	6.4710*	4.6061*	6.1528*	6.7921*	7.8531
	MAE	11.689*	5.0985*	4.0951	5.0302	4.5659	5.9743
	MedAPE	0.7988*	0.8003*	0.957	2.0264	2.0681	4.1406
	MedSE	33.252*	24.353	13.994*	19.128	14.968	15.924
Prudential	RMSE	32.673*	27.037	8.1877	5.4784*	8.8741*	8.3273*
	MAE	13.318	13.388*	6.104	4.6996	5.3039	5.8212*
	MedAPE	0.922	0.8237*	2.2195	3.87	1.1503*	0.6344
	MedSE	16.500*	55.516*	24.178	16.613	6.9422	17.639
RMC	RMSE	34.033*	14.328	7.1706	7.7482	15.281*	14.373
	MAE	19.802	11.036	6.8475	6.038	9.1261	9.0995
	MedAPE	1.829	3.85	15.671	12.918	1.2637*	4.3323
	MedSE	93.906*	92.883*	50.023	32.489	41.629	31.535
Rank Group	RMSE	21.737	16.253	19.493*	9.7885*	14.61	24.702
	MAE	13.779	12.371*	9.3313	8.4217*	8.0663	11.834
	MedAPE	0.8962	2.125	1.0236	1.9696*	1.0597	1.0079
	MedSE	77.454	72.976*	22.464	58.644*	23.338*	26.132*
Reed International	RMSE	10.801	7.4886	5.8175	14.104	10.177	14.630*
	MAE	8.0172	5.7265	4.9245	7.9613*	7.1776	9.2407
	MedAPE	1.6998	0.8467	0.7594*	1.9254*	7.9278	2.2753
	MedSE	27.531	25.983	22.798*	19.718*	21.776	26.689

Table 4.16 (continued). Forecast Error Statistics for the CGARCH/ACGARCH Model (Rolling Equation Estimation)

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Reuters	RMSE	39.754	28.022	7.8858	13.296*	28.819*	7.9777*
	MAE	22.137	20.514	6.9966	9.1624	14.813	6.1449
	MedAPE	1.0768	0.8896*	4.74	1.2637	1.7278	0.4780*
	MedSE	71.623	218.68	57.183	39.38	26.832	33.637
Rio Tinto	RMSE	9.734	5.7464	3.6325*	4.7095	4.5552	7.2878*
	MAE	7.8392	4.5415	2.9195*	3.5864	3.1515	4.9952
	MedAPE	1.6818	0.975	1.3608*	2.3027*	1.0141*	3.3296
	MedSE	33.823	19.29	7.4537*	8.3248*	6.7236	10.247
Royal & Sun Alliance Ins.	RMSE	40.712	23.255	21.036*	8.8772*	14.251	10.822*
	MAE	22.134	16.420*	13.645*	8.7502*	8.2163*	9.0060*
	MedAPE	0.8371	1.4196*	1.7739*	7.0822*	0.6699	9.1751*
	MedSE	99.64	113.22*	105.72*	80.471*	28.399	63.388
Royal Bank of Scotland	RMSE	18.802	14.806*	15.224	12.622*	15.507	8.2088
	MAE	12.346	9.5370*	10.955	9.3434*	10.51	6.1225
	MedAPE	0.9420*	0.8955*	0.6159	3.4691*	8.3589	0.772
	MedSE	57.922	43.921*	68.040*	63.757*	61.407	30.298
Sainsbury	RMSE	10.334*	10.032	4.2724	6.5366	10.194	16.896*
	MAE	4.9343*	5.2639	3.5399	4.4857	5.2262	6.1349*
	MedAPE	2.2563	0.8982*	0.6531*	1.3830*	5.0292	2.3213*
	MedSE	11.539	7.5790*	10.608	13.206	10.696*	6.2046*
Standard Chartered	RMSE	22.995*	28.991*	14.886	9.7094	44.722	10.578*
	MAE	17.568	21.508*	11.547*	7.9344	25.278	9.4287*
	MedAPE	1.0551*	1.0105*	1.3064	1.8296	3.3258	3.5621*
	MedSE	189.40*	270.39*	102.62*	54.998	204.77	102.23*
Unilever	RMSE	19.195*	18.984	8.3515*	5.6196	10.665*	13.602
	MAE	10.811*	10.900*	5.4100*	4.5398	7.3187	8.4181
	MedAPE	0.83	2.2772*	2.2662*	1.4594	0.8436*	2.6519
	MedSE	20.413*	44.992*	17.868*	15.6	23.206	23.798

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Appendix 4

Table 5.1. GARCH/GJR Volume Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} + \delta_v V_t$$

where D_{t-1} = 1 when ϵ_{t-1} is negative and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero. V_t is the volume of trade in millions of shares.

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1	δ_v
Asda	-0.0034 (0.0033)	0.0065 (0.0204)	-0.0107* (0.0035)	0.1506* (0.0229)	_	0.0992* (0.0170)	_	_	0.4281* (0.0220)
Associated British Foods	0.0110 (0.0171	0.1229* (0.0222)	0.2063* (0.0448)	0.1810* (0.0396)	0.1586* (0.0569)	0.0022 (0.0348)	_	_	1.0461* (0.0905)
BAA	0.0068 (0.0061)	0.0706* (0.0173)	0.0516* (0.0053)	0.1135* (0.0184)	0.0275* (0.0053)	-0.0257* (0.0028)	_	_	0.5288* (0.0206
BAT Industries	-0.0084 (0.0142)	0.0244 (0.0131)	0.2346* (0.0295)	0.0223* (0.0044)	_	-0.0500* (0.0066)	_	_	0.2055* (0.0075)
BOC	0.0072 (0.0116)	0.0484* (0.0186)	0.1637* (0.0410)	0.0816* (0.0188)	_	-0.0246* (0.0065)	_	_	1.2455* (0.0580)
BG	-0.0016 (0.0062)	0.0361* (0.0183)	0.2069* (0.0346)	0.1060* (0.0269)	_	-0.0132* (0.0024)	_	_	0.0957* (0.0051)
BT	0.0029 (0.0082)	0.0557* (0.0165)	0.2130* (0.0504)	0.0415* (0.0100)	0.0300* (0.0144)	-0.0870* (0.0269)	_	_	0.1703* (0.0111)
Barclays	0.0013 (0.0013)	0.0792* (0.0186)	-0.0002* (0.0001)	0.1921* (0.0245)	_	0.0182* (0.0037)	_	_	0.5166* (0.0221)
Bass	-0.0197 (0.0073)	0.0816* (0.0183)	0.0607* (0.0125)	0.1417* (0.0252)	0.0156* (0.0072)	-0.0234* (0.0037)	_	_	0.7860* (0.0405)
Blue Circle	-0.0036 (0.0026)	0.0896* (0.0162)	-0.0001 (0.0001)	0.1510* (0.0360)	0.1346* (0.0425)	-0.0008 (0.0007)	_	_	1.2692* (0.0812)
Boots	0.0101 (0.0085)	0.0344* (0.0170)	0.0683* (0.0106)	0.0355* (0.0134)	_	-0.0080* (0.0013)	_	_	0.8637* (0.0299)
British Airways	-0.0065* (0.0025)	0.0414* (0.0145)	0.0000 (0.0000)	0.0441* (0.0192)	-0.0009* (0.0004)	0.0156* (0.0024)	_	0.0433* (0.0216)	0.7005* (0.0263)
CGU	-0.0022 (0.0021)	0.0433* (0.0175)	-0.0001 (0.0001)	0.0531* (0.0162)	0.0177* (0.0046)	0.0083 (0.0046)	_	_	1.7024* (0.0731)

Table 5.1 (continued). GARCH/GJR Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1	δ_v
Cadbury Schweppes	-0.0196* (0.0054)	0.0559* (0.0155)	0.0902* (0.0061)	0.0421* (0.0089)	_	-0.0308* (0.0024)	_	_	0.4047* (0.0144)
Diageo	-0.0005 (0.0005)	0.0598* (0.0186)	-0.0017* (0.0004)	0.0817* (0.0087)	_	0.0757* (0.0090)	_	0.0744* (0.0234)	0.3860* (0.0192)
EMI	0.0004 (0.0058)	0.0640* (0.0199)	0.0988* (0.0387)	0.1052* (0.0344)	0.0853* (0.0207)	-0.0251* (0.0103)	_	_	0.5353* (0.0304)
Enterprise Oil	-0.0028 (0.0015)	0.0432* (0.0078)	0.0001* (2e-05)	0.1187* (0.0219)	_	-4e-05* (8e-06)	_	_	2.0488* (0.0931)
General Electric	-0.0009 (0.0008)	0.0581* (0.0166)	-0.0010* (0.0002)	0.0243* (0.0031)	_	0.0564* (0.0053)	_	_	0.2740* (0.0112)
Glaxo Wellcome	0.0092 (0.0095)	0.0107 (0.0146)	0.3022* (0.0410)	0.0359* (0.0097)	_	-0.0768* (0.0112)	_	_	0.4072* (0.0170)
ICI	-0.0070* (0.0017)	0.0906* (0.0076)	4e-05* (5e-06)	0.0981* (0.0132)	_	-0.0001* (2e-05)	_	_	0.6159* (0.0268)
Ladbroke	-0.0131 (0.0099)	-0.0002 (0.0140)	0.0716* (0.0107)	0.1017* (0.0121)	_	-0.0151* (0.0022)	_	_	0.9744* (0.0370)
Land Securities	0.0064 (0.0075)	-0.0042 (0.0031)	0.0078* (0.0021)	-0.0062* (0.0015)	_	0.0382* (0.0116)	_	_	1.1358* (0.0437)
Legal & General	0.0010 (0.0010)	0.0801* (0.0206)	0.1125* (0.0340)	0.1395* (0.0239)	0.0907* (0.0196)	-0.0165* (0.0048)	_	_	0.1759* (0.0102)
Marks & Spencer	0.0091 (0.0054)	0.0534* (0.0177)	0.1703* (0.0354)	0.1078* (0.0177)	0.0193* (0.0038)	-0.0722* (0.0140)	_	_	0.3527* (0.0168)
Natwest Bank	0.0036 (0.0036)	0.0545* (0.0198)	-0.0938* (0.0153)	0.1479* (0.0254)	_	0.3963* (0.0308)	_	_	0.3472* (0.0213)
Pearson	-0.0017* (0.0007)	0.0438* (0.0050)	2e-06* (8e-07)	0.1341* (0.0205)	_	7e-06* (3e-06)	_	_	1.6140* (0.0722)
Prudential	-0.0003 (0.0003)	0.0580* (0.0190)	-0.0020* (0.0006)	0.1055* (0.0191)	_	0.0643* (0.0095)	_	_	0.5870* (0.0233)
RMC	-0.0113 (0.0097)	0.0671* (0.0187)	0.0828* (0.0202)	0.0849* (0.0193)	0.0747* (0.0262)	-0.0149* (0.0042)	_	_	4.3776* (0.4028)
Rank Group	-0.0026* (0.0009)	0.0440* (0.0055)	1e-05* (3e-06)	0.1210* (0.0194)	_	3e-05* (8e-06)	_	_	1.0516* (0.0404)
Reckitt & Colman	-0.0384* (0.0106)	0.0856* (0.0131)	0.1070* (0.0196)	0.1199* (0.0224)	_	-0.0249* (0.0036)	-0.0192* (0.0052)	_	1.5562* (0.0732)
Reed International	-0.0013 (0.0012)	0.0400* (0.0109)	0.0012* (0.0002)	0.0215* (0.0040)	_	-0.0006 (0.0001)	_	0.0674* (0.0194)	0.7283* (0.0270)

Table 5.1 (continued). GARCH/GJR Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1	δ_v
Reuters	0.0172* (0.0036)	0.0787* (0.0149)	0.0000 (0.0002)	0.0674* (0.0127)	0.0161* (0.0031)	-0.0013 (0.0003)	_	-0.0385* (0.0118)	0.6471* (0.0225)
Rio Tinto	0.0012 (0.0012)	0.0661* (0.0161)	0.0000 (0.0000)	0.1364* (0.0263)	0.1030* (0.0164)	-0.0022* (0.0006)	_	_	0.7943* (0.0333)
Royal & Sun Alliance Ins.	-0.0255 (0.0194)	0.0557* (0.0171)	0.3215* (0.0167)	0.0809* (0.0196)	_	-0.0370* (0.0019)	_	_	1.2371* (0.0564)
Royal Bank of Scotland	-0.0020 (0.0020)	0.0878* (0.0203)	-0.0019 (0.0020)	0.1006* (0.0334)	0.0810* (0.0264)	0.0621 (0.0322)	_	_	1.1689* (0.0638)
Sainsbury	0.0065 (0.0149)	0.0572* (0.0153)	0.2607* (0.0341)	0.0283* (0.0053)	_	-0.0835* (0.0125)	_	_	0.7214* (0.0244)
Scottish & Newcastle	0.0000 (0.0000)	0.0483* (0.0164)	-5e-05* (1e-05)	0.1463* (0.0198)	_	0.0101* (0.0014)	_	_	1.3513* (0.0657)
Standard Chartered	-0.0286* (0.0087)	0.0595* (0.0171)	0.0096* (0.0016)	0.1431* (0.0186)	_	-0.0010* (0.0001)	_	_	1.0572* (0.0452)
Unilever	0.0015* (0.0005)	0.0510* (0.0035)	0.0000 (0.0000)	0.1431* (0.0177)	_	1e-06 (1e-06)	_	_	0.1890* (0.0085)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level. The mean equations for BAT Industries and RMC include a dummy variable term to remove the effect of one-off large outliers (BAT Industries 25.9 per cent return on 11/7/1989 and RMC 19.2 per cent return on 1/6/1998).

Table 5.2. GARCH/GJR Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Asda	0.0438	3.9661	12.935	0.1491	181.75*	286.38*	0.1488	33.667*	20.643*
Associated British Foods	0.2469	10.883	13.871	0.2564	22.587*	67.297*	0.2559	4.6118*	6.1498*
BAA	0.0511	3.6001	5.6566	1.8058	30.266*	100.22*	1.8036	5.4437*	7.6642*
BAT Industries	0.7913	25.682*	42.009*	0.0824	34.502*	89.664*	0.0823	6.2935*	6.9932*
BOC	0.1245	5.2544	12.711	3.6505	97.374*	259.78*	3.6494	16.642*	17.726*
BG	0.0665	13.764*	22.568*	0.0004	61.518*	157.28*	0.0004	11.671*	12.231*
BT	1.3118	5.5273	13.485	0.7371	17.953*	46.137*	0.7364	3.4000*	3.7319*
Barclays	0.2089	5.7827	18.218	2.9509	126.50*	220.41*	2.9544	25.975*	17.619*
Bass	2.2533	13.149*	31.785*	1.8714	19.585*	110.85*	2.3270	4.3644*	11.971*
Blue Circle	0.0037	6.3574	12.515	0.0092	18.129*	41.197*	0.0092	3.6274*	4.4840*
Boots	1.9828	4.2731	31.281*	5.4382*	64.700*	111.20*	5.4789*	11.381*	8.0084*
British Airways	1.3045	3.0878	14.661	3.4886	49.242*	95.352*	3.4865	8.4513*	6.7673*
CGU	0.0051	6.9570	16.022	1.6064	65.750*	150.86*	1.6064	11.760*	10.921*
Cadbury Schweppes	1.4691	15.446*	36.287*	11.763*	97.071*	198.96*	11.966*	15.487*	12.124*
Diageo	0.3914	14.222*	26.325*	0.0630	38.613*	71.696*	0.0645	7.5542*	5.8858*
EMI	0.3398	3.1534	20.545*	0.0194	124.08*	233.68*	0.0194	27.157*	20.456*
Enterprise Oil	8.7286*	15.196*	26.159*	0.3120	37.543*	66.847*	0.3114	7.0230*	5.4701*
General Electric	0.0683	10.139	29.982*	0.0259	37.441*	93.387*	0.0336	9.2693*	10.027*
Glaxo Wellcome	2.1278	21.152*	38.273*	0.0744	89.489*	195.95*	0.0743	16.582*	14.054*
ICI	0.0322	4.1211	13.135	0.3091	80.648*	137.92*	0.4028	19.533*	13.527*
Ladbroke	2.0096	13.336*	13.652	3.2296	77.598*	196.08*	3.2380	13.297*	13.377*
Land Securities	1.3360	6.6554	14.891	39.862*	63.936*	103.20*	40.360*	10.973*	8.1011*
Legal & General	0.0012	3.2250	15.291	0.6857	37.795*	143.53*	0.6848	7.3455*	12.525*
Marks & Spencer	0.2433	15.464*	34.131*	2.0545	29.119*	82.706*	2.0519	5.4068*	6.5808*
Natwest Bank	0.0544	12.885*	35.884*	0.1143	41.924*	92.386*	0.1141	8.5198*	8.1877*
Pearson	0.0913	9.2415	21.835*	0.2552	204.87*	390.73*	0.2552	36.469*	25.954*
Prudential	0.6128	14.452*	32.125*	0.0072	68.356*	115.96*	0.0072	12.438*	8.9069*
RMC	0.8056	8.7211	15.355	1.3427	6.0173	43.707*	1.3407	1.1297	3.9834*
Rank Group	4.5916*	8.1911	11.388	5.2957*	59.027*	100.58*	5.3538*	10.915*	7.9660*
Reckitt & Colman	2.9295	8.3566	15.545	1.0776	62.293*	90.948*	1.0758	12.218*	7.3113*
Reed International	5.6456*	10.804	12.038	4.3240*	97.473*	159.42*	4.3220*	16.539*	10.988*

Table 5.2 (continued). GARCH/GJR Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Reuters	6.5642*	29.064*	32.775*	6.6139*	84.899*	164.17*	6.6926*	14.367*	11.606*
Rio Tinto	0.1061	15.616*	25.677*	2.3117	145.33*	354.95*	2.3125	27.770*	26.992*
Royal & Sun Alliance Ins.	1.2143	12.419*	24.324*	2.1873	134.06*	252.74*	2.1843	22.752*	17.625*
Royal Bank of Scotland	0.3336	5.7843	21.930*	2.1253	39.205*	67.848*	2.1227	7.3961*	5.4294*
Sainsbury	1.8435	11.318*	18.924*	1.1090	36.136*	100.49*	1.1088	6.3097*	7.5067*
Scottish & Newcastle	0.0000	13.560*	17.085	0.0820	57.356*	116.50*	0.0829	10.587*	8.6780*
Standard Chartered	1.6342	5.9630	19.914*	0.5437	125.61*	189.82*	0.5432	22.517*	13.515*
Unilever	3.4467	9.5328	23.874*	0.0099	55.492*	143.44*	0.0099	10.187*	11.049*

Notes: Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 5.3. GARCH/GJR Lagged Volume Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} + \delta_v V_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero. V_{t-1} is the volume of trade in millions of shares for period t - 1.

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1	δ_v
Asda	0.0681* (0.0323)	0.0139 (0.0231)	0.1581* (0.0563)	0.1101* (0.0465)	_	0.8871* (0.0346)	_	_	-0.0107* (0.0049)
Associated British Foods	0.0409* (0.0180)	0.1272* (0.0229)	0.0076 (0.0055)	0.1351* (0.0296)	-0.1329* (0.0290)	0.9798* (0.0062)	_	0.0324* (0.0098)	-0.0052 (0.0062)
BAA	0.0515* (0.0215)	0.1000* (0.0213)	0.0137 (0.0074)	0.1989* (0.0380)	-0.1797* (0.0375)	0.9734* (0.0094)	_	_	-0.0006 (0.0012)
BAT Industries	0.0399 (0.0268)	0.0568* (0.0208)	0.0604 (0.0314)	0.0469* (0.0116)	_	0.8800* (0.0275)	_	_	0.0112* (0.0039)
BOC	0.0299 (0.0227)	0.0707* (0.0211)	0.0064 (0.0099)	0.0268* (0.0066)	_	0.9643* (0.0082)	_	_	0.0072 (0.0095)
BG	0.0251 (0.0254)	0.0742* (0.0216)	0.0380 (0.0304)	0.0675* (0.0178)	_	0.8904* (0.0243)	_	_	0.0034 (0.0023)
BT	0.0322 (0.0223)	0.1105* (0.0212)	0.0214 (0.0143)	0.1284* (0.0336)	-0.0956* (0.0330)	0.9484* (0.0196)	_	_	0.0014 (0.0013)
Barclays	0.0506 (0.0259)	0.1178* (0.0213)	0.0691* (0.0223)	0.0759* (0.0141)	_	0.9068* (0.0177)	_	_	-0.0050 (0.0052)
Bass	0.0166 (0.0214)	0.1197* (0.0219)	0.0063 (0.0058)	0.1782* (0.0447)	-0.1646* (0.0438)	0.9856* (0.0062)	_	_	-0.0024 (0.0030)
Blue Circle	0.0018 (0.0289)	0.1144* (0.0272)	0.0181 (0.0215)	0.1155* (0.0398)	-0.1059* (0.0420)	0.9665* (0.0074)	_	0.0355* (0.0179)	0.0025 (0.0104)
Boots	0.0521* (0.0250)	0.0766* (0.0203)	0.0319* (0.0111)	0.0369* (0.0084)	_	0.9486* (0.0111)	_	_	-0.0021 (0.0026)
British Airways	0.0450 (0.0282)	0.0941* (0.0220)	0.0298 (0.0184)	0.1177* (0.0317)	-0.1080* (0.0304)	0.9733* (0.0078)	_	0.0226* (0.0098)	-0.0039 (0.0043)
CGU	0.0395 (0.0255)	0.0862* (0.0211)	0.0563* (0.0239)	0.0744* (0.0133)	_	0.8857* (0.0206)	_	_	0.0224 (0.0119)
Cadbury Schweppes	0.0242 (0.0236)	0.0951* (0.0193)	0.1408* (0.0304)	0.0760* (0.0155)	_	0.8811* (0.0239)	_	_	-0.0129* (0.0018)
Diageo	0.0505* (0.0247)	0.0824* (0.0214)	0.0148 (0.0143)	0.0123* (0.0059)	_	0.9593* (0.0123)	_	0.0400* (0.0137)	0.0020 (0.0024)

Table 5.3 (continued). GARCH/GJR Lagged Volume Model Conditional Mean and Variance Specifications									
Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1	δ_v
EMI	0.0252 (0.0220)	0.1097* (0.0206)	-0.0021 (0.0079)	0.0568* (0.0249)	-0.0567* (0.0247)	0.9829* (0.0055)	_	0.0292* (0.0085)	0.0032 (0.0022)
Enterprise Oil	0.0169 (0.0330)	0.1032* (0.0299)	0.0497* (0.0148)	0.0855* (0.0255)	_	0.9113* (0.0124)	_	_	-0.0099* (0.0018)
General Electric	0.0302 (0.0257)	0.0860* (0.0196)	0.0500* (0.0252)	0.0533* (0.0132)	_	0.9170* (0.0207)	_	_	0.0019 (0.0035)
Glaxo Wellcome	0.0749* (0.0281)	0.0674* (0.0217)	0.0990* (0.0236)	0.0471* (0.0133)	_	0.9401* (0.0133)	_	_	-0.0121* (0.0032)
ICI	0.0223 (0.0237)	0.1191* (0.0220)	0.0260 (0.0138)	0.0432* (0.0109)	_	0.9464* (0.0115)	_	_	-0.0013 (0.0044)
Ladbroke	-0.0085 (0.0319)	0.0529* (0.0254)	0.0362* (0.0177)	0.1431* (0.0444)	-0.1381* (0.0440)	0.9610* (0.0113)	_	0.0566* (0.0253)	-0.0021 (0.0033)
Land Securities	0.0208 (0.0193)	0.0756* (0.0207)	0.0309 (0.0162)	0.0599* (0.0129)	_	0.9105* (0.0198)	_	_	0.0062 (0.0124)
Legal & General	0.0491 (0.0260)	0.1020* (0.0220)	0.0382* (0.0139)	0.1207* (0.0373)	-0.0956* (0.0370)	0.9687* (0.0076)	_	_	-0.0020* (0.0009)
Marks & Spencer	0.0179 (0.0245)	0.0868* (0.0212)	0.0479 (0.0245)	0.1297* (0.0347)	-0.0938* (0.0338)	0.9459* (0.0147)	_	_	-0.0031 (0.0048)
Natwest Bank	0.0369 (0.0277)	0.0673* (0.0221)	0.0469 (0.0300)	0.0906* (0.0197)	_	0.8838* (0.0194)	_	_	0.0094 (0.0087)
Pearson	0.0378* (0.0138)	0.0460* (0.0192)	1.2656* (0.4300)	0.1233* (0.0290)	_	0.5671* (0.1384)	_	_	-0.0242* (0.0007)
Prudential	0.0547 (0.0285)	0.0774* (0.0211)	0.1930* (0.0757)	0.0813* (0.0194)	_	0.8413* (0.0396)	_	_	-1e-05 (0.0122)
RMC	0.0279 (0.0235)	0.1428* (0.0240)	-0.0059 (0.0181)	0.0980* (0.0340)	-0.0756* (0.0324)	0.9772* (0.0080)	_	_	0.0210 (0.0317)
Rank Group	0.0138 (0.0276)	0.0704* (0.0223)	0.1127* (0.0383)	0.0969* (0.0207)	_	0.8529* (0.0252)	_	_	0.0094 (0.0130)
Reckitt & Colman	0.0277 (0.0200)	0.1395* (0.0221)	0.0757* (0.0295)	0.1629* (0.0295)	-0.0808* (0.0314)	0.3810* (0.1581)	0.4864* (0.1315)	_	-0.0071 (0.0143)
Reed International	0.0215 (0.0242)	0.1041* (0.0218)	0.0146 (0.0091)	0.1455* (0.0375)	-0.1347* (0.0358)	0.9671* (0.0071)	_	0.0318* (0.0156)	-0.0004 (0.0043)
Reuters	0.0565* (0.0272)	0.1670* (0.0249)	0.0265* (0.0132)	0.1841* (0.0712)	-0.1798* (0.0689)	0.9627* (0.0086)	_	0.0370* (0.0125)	0.0028 (0.0034)
Rio Tinto	0.0145 (0.0238)	0.0997* (0.0212)	0.0304* (0.0140)	0.0833* (0.0339)	-0.0703* (0.0345)	0.9560* (0.0103)	_	0.0416* (0.0139)	-0.0057 (0.0050)

Table 5.3 (continued). GARCH/GJR Lagged Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	β_2	γ_1	δ_v
Royal & Sun Alliance Ins.	0.0661* (0.0315)	0.0962* (0.0213)	0.0003 (0.0079)	0.0248* (0.0098)	_	0.9732* (0.0098)	_	_	0.0046 (0.0034)
Royal Bank of Scotland	0.0480 (0.0285)	0.1104* (0.0226)	0.0107 (0.0113)	0.1339* (0.0318)	-0.1093* (0.0300)	0.9697* (0.0093)	_	_	0.0037 (0.0039)
Sainsbury	0.0339 (0.0249)	0.1284* (0.0210)	0.0420* (0.0173)	0.0457* (0.0118)	_	0.9168* (0.0212)	_	_	0.0132 (0.0097)
Scottish & Newcastle	0.0717* (0.0330)	0.0663* (0.0243)	0.0926 (0.0479)	0.1423* (0.0369)	_	0.8450* (0.0214)	_	_	-0.0088 (0.0327)
Standard Chartered	0.0859* (0.0301)	0.1071* (0.0215)	0.0477* (0.0143)	0.0473* (0.0087)	_	0.9467* (0.0087)	_	_	-0.0062* (0.0016)
Unilever	0.0497* (0.0201)	0.1451* (0.0205)	0.0242* (0.0086)	0.0387* (0.0078)	_	0.9515* (0.0093)	_	_	-0.0020* (0.0010)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level. The mean equations for BAT Industries and RMC include a dummy variable term to remove the effect of one-off large outliers (BAT Industries 25.9 per cent return on 11/7/1989 and RMC 19.2 per cent return on 1/6/1998).

Table 5.4. GARCH/GJR Lagged Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Asda	2.5078	4.4419	10.923	1.1041	1.8406	3.4408	1.1022	0.3732	0.3350
Associated British Foods	0.0624	9.2541	16.573	0.3736	5.0471	9.0791	0.3729	0.9496	0.8157
BAA	0.3998	4.7016	6.8998	0.0432	6.5504	8.8425	0.0431	1.3586	0.9499
BAT Industries	0.0737	10.729	18.647*	0.0019	2.5680	13.378	0.0019	0.5186	1.3173
BOC	0.2173	5.3828	9.9881	0.2591	1.2053	4.7728	0.2586	0.2383	0.4871
BG	0.1992	3.5623	11.250	2.1494	4.2315	7.9037	2.1468	0.8842	0.8101
BT	0.0953	3.8632	9.8133	0.0015	1.2259	8.3375	0.0015	0.2427	0.8475
Barclays	0.0830	2.6913	10.391	0.1531	1.1398	4.4616	0.1528	0.2292	0.4424
Bass	1.9583	10.465	21.064*	0.0099	0.9201	8.5732	0.0100	0.1834	0.8180
Blue Circle	0.0033	5.6705	14.042	0.0205	4.0536	5.9513	0.0205	0.8155	0.7001
Boots	0.0794	1.9405	24.190*	0.9431	7.6611	10.860	0.9415	1.5313	1.0940
British Airways	0.1304	2.9073	10.409	0.6179	7.3227	9.6281	0.6168	1.5053	0.9803
CGU	0.1486	7.4534	16.578	3.8384	6.2804	11.869	3.8354	1.2952	1.1934
Cadbury Schweppes	0.0028	6.2103	16.896	2.0579	5.8353	8.4655	2.0593	1.1557	0.8349
Diageo	0.0423	6.9922	19.480*	1.5716	2.5141	2.7564	1.5692	0.4916	0.2715
EMI	0.0077	4.9018	10.637	0.0054	0.1592	6.7443	0.0053	0.0318	0.6711
Enterprise Oil	2.5541	6.1268	13.793	0.0220	0.7735	1.3159	0.0220	0.1534	0.1288
General Electric	0.1454	4.9758	19.272*	0.4616	4.3165	7.8915	0.4678	0.9512	0.8959
Glaxo Wellcome	0.3365	8.9824	17.976	0.0021	1.2720	4.8452	0.0021	0.2523	0.4712
ICI	0.1337	5.2700	6.7238	1.8852	2.4549	5.9344	1.8833	0.4860	0.6146
Ladbroke	0.0741	7.3237	10.642	0.3834	4.2310	6.4969	0.3827	0.8262	0.6425
Land Securities	0.0015	6.0634	9.7932	1.6964	1.9048	4.8402	1.6939	0.3879	0.4820
Legal & General	0.2072	3.1417	15.825	0.0026	2.2408	5.8308	0.0026	0.4460	0.5617
Marks & Spencer	0.0422	8.4077	21.369*	0.1276	1.9020	3.4342	0.1273	0.3787	0.3481
Natwest Bank	0.1237	8.2418	22.864*	1.2985	5.2304	8.9364	1.2964	1.0847	0.9122
Pearson	0.1384	7.6178	13.038	3.0310	20.562*	61.699*	3.0339	3.6917*	5.2288*
Prudential	0.2677	14.964	27.024*	0.7688	2.3017	4.8861	0.7674	0.4467	0.4681
RMC	0.7798	5.7745	9.6218	1.9686	2.1879	3.5848	1.9658	0.4285	0.3500
Rank Group	0.1318	3.4900	11.489	0.6817	7.5894	9.5898	0.6807	1.4650	0.9242
Reckitt & Colman	0.0000	5.9146	10.985	0.4687	0.7664	5.4146	0.4678	0.1544	0.5426
Reed International	0.3208	3.4437	3.6255	0.4024	1.0834	3.3980	0.4017	0.2129	0.3416

Table 5.4 (continued). GARCH/GJR Lagged Volume Model Residual Diagnostics									
Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Reuters	0.5022	12.564*	14.780	0.0289	2.3126	3.7104	0.0289	0.4629	0.3971
Rio Tinto	0.3893	8.2055	10.491	0.1901	3.8340	11.487	0.1898	0.7733	1.2112
Royal & Sun Alliance Ins.	0.8493	5.1675	13.280	0.0155	0.2804	1.8469	0.0155	0.0561	0.1831
Royal Bank of Scotland	0.0852	6.9773	13.173	0.0238	2.1674	3.3051	0.0238	0.4291	0.3151
Sainsbury	0.0698	3.2601	8.7487	0.0877	2.2903	4.2060	0.0875	0.4571	0.4078
Scottish & Newcastle	0.1911	5.2622	7.7772	0.0320	0.2317	0.5429	0.0319	0.0464	0.0550
Standard Chartered	0.8419	3.8697	17.927	3.4765	9.8464	12.868	3.4749	1.8669	1.2510
Unilever	0.0062	2.4675	6.8000	0.6562	4.3423	7.6206	0.6551	0.8367	0.7066

Notes: Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 5.5. GARCH/GJR Unexpected Volume Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1} + \delta_v V_t^*$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero. V_t^* is the innovation in the volume of trade, that is, the residuals of a fitted ARMA model for volume of trade.

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	γ_1	δ_v
Asda	0.0165 (0.0146)	0.0177 (0.0211)	1.4616* (0.1034)	0.2519* (0.0433)	_	0.3869* (0.0319)	_	0.1515* (0.0097)
Associated British Foods	0.0336 (0.0182)	0.1285* (0.0219)	0.0335* (0.0112)	0.0278* (0.0110)	_	0.9178* (0.0161)	0.0605* (0.0198)	0.1042* (0.0277)
BAA	0.0243 (0.0174)	0.0714* (0.0187)	0.8966* (0.0371)	0.1776* (0.0193)	0.0703* (0.0094)	0.1090* (0.0073)	_	0.1826* (0.0063)
BAT Industries	0.0161 (0.0225)	0.0378* (0.0184)	0.2921* (0.0494)	0.0511* (0.0159)	_	0.8138* (0.0365)	_	0.0817* (0.0050)
BOC	0.0134 (0.0109)	0.0764* (0.0205)	0.3402* (0.0301)	0.1488* (0.0164)	_	0.6309* (0.0150)	_	0.5708* (0.0366)
BG	0.0059 (0.0057)	0.0512* (0.0203)	0.5274* (0.0300)	0.1198* (0.0180)	_	0.6314* (0.0113)	_	0.0594* (0.0031)
BT	0.0047 (0.0238)	0.0864* (0.0220)	0.5705* (0.1892)	0.1228* (0.0320)	_	0.5155* (0.1460)	_	0.0461* (0.0083)
Barclays	0.0518* (0.0220)	0.0885* (0.0177)	0.5778* (0.0339)	0.1976* (0.0187)	_	0.5609* (0.0139)	_	0.2096* (0.0086)
Bass	0.0078 (0.0072)	0.1104* (0.0206)	0.6055 (0.0306)	0.1438* (0.0216)	_	0.4501* (0.0112)	_	0.4331* (0.0220)
Blue Circle	-0.0449 (0.0277)	0.0959* (0.0255)	1.2044* (0.1376)	0.1297* (0.0382)	0.1476* (0.0555)	0.3240* (0.0480)	_	0.6928* (0.0645)
Boots	0.0075 (0.0062)	0.0354* (0.0157)	1.7114* (0.0630)	0.0496* (0.0114)	_	0.0431* (0.0003)	_	0.8428* (0.0311)
British Airways	0.0006 (0.0006)	0.0742* (0.0197)	0.7620* (0.0628)	0.0618 (0.0341)	0.0550* (0.0233)	0.4911* (0.0289)	0.1020* (0.0355)	0.3507* (0.0225)
CGU	0.0353 (0.0250)	0.0827* (0.0208)	0.1236* (0.0279)	0.0743* (0.0139)	_	0.8711* (0.0216)	_	0.0956* (0.0227)
Cadbury Schweppes	0.0097 (0.0148)	0.0867* (0.0198)	0.5914* (0.0408)	0.0901* (0.0177)	_	0.5828* (0.0199)	_	0.1212* (0.0072)
Diageo	0.0277 (0.0177)	0.0791* (0.0219)	0.5837* (0.1234)	0.1447* (0.0234)	_	0.5419* (0.0793)	_	0.1537* (0.0178)

Table 5.5 (continued). GARCH/GJR Unexpected Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	γ_1	δ_v
EMI	0.0119 (0.0100)	0.0645* (0.0188)	0.6708* (0.0448)	0.0663* (0.0212)	0.1250* (0.0240)	0.3459* (0.0074)	_	0.3470* (0.0201)
Enterprise Oil	-0.0379* (0.0122)	0.0655* (0.0200)	2.6890* (0.1284)	0.1424* (0.0249)	_	0.0155* (1e-05)	_	1.9287* (0.0921)
General Electric	-0.0122 (0.0105)	0.0689* (0.0182)	0.6063* (0.0378)	0.0860* (0.0161)	_	0.5594* (0.0239)	_	0.1563* (0.0062)
Glaxo Wellcome	0.0106 (0.0073)	0.0359* (0.0178)	1.0592* (0.0386)	0.0713* (0.0114)	_	0.4295* (0.0105)	_	0.2790* (0.0108)
ICI	-0.0045 (0.0201)	0.1283* (0.0206)	0.8011* (0.1117)	0.1908* (0.0304)	_	0.3117* (0.0757)	_	0.2277* (0.0137)
Ladbroke	-0.0135 (0.0114)	0.0233 (0.0190)	1.5488* (0.0679)	0.0888* (0.0248)	0.1032* (0.0145)	0.3120* (0.0155)	_	0.4621* (0.0204)
Land Securities	0.0097 (0.0085)	0.0364 (0.0196)	0.5438* (0.0582)	0.0385 (0.0204)	_	0.4824* (0.0522)	_	0.5369* (0.0252)
Legal & General	0.0069 (0.0058)	0.0858* (0.0193)	0.7436* (0.0535)	0.1591* (0.0280)	0.0883* (0.0257)	0.4184* (0.0119)	_	0.0747* (0.0055)
Marks & Spencer	0.0183* (0.0080)	0.0602* (0.0194)	1.0025* (0.1120)	0.0936* (0.0192)	_	0.3088* (0.0637)	_	0.2589* (0.0123)
Natwest Bank	0.0332 (0.0203)	0.0671* (0.0200)	1.0403* (0.0988)	0.1198* (0.0259)	_	0.4829* (0.0495)	_	0.3038* (0.0119)
Pearson	0.0021 (0.0021)	0.0417 (0.0219)	1.4327* (0.0659)	0.2126* (0.0287)	_	0.0987* (0.0157)	_	0.8202* (0.0377)
Prudential	0.0324 (0.0202)	0.0632* (0.0199)	1.1234* (0.0926)	0.1092* (0.0229)	_	0.4006* (0.0410)	_	0.3809* (0.0210)
RMC	0.0120 (0.0246)	0.1000* (0.0204)	1.3338* (0.1630)	0.1160* (0.0410)	0.0968* (0.0361)	0.2198* (0.0251)	_	2.8351* (0.4181)
Rank Group	0.0056 (0.0055)	0.0639* (0.0209)	0.8577* (0.1190)	0.1228* (0.0266)	_	0.4689* (0.0646)	_	0.3673* (0.0204)
Reckitt & Colman	0.0063 (0.0060)	0.1464* (0.0211)	0.5844* (0.0686)	0.1574* (0.0323)	_	0.3978* (0.0566)	_	0.5235* (0.0360)
Reed International	0.0123 (0.0104)	0.0940* (0.0190)	0.9381* (0.0551)	0.0619* (0.0248)	0.0778* (0.0182)	0.2521* (0.0064)	0.1009* (0.0418)	0.3678* (0.0213)
Reuters	0.0372 (0.0206)	0.1182* (0.0190)	1.0177* (0.0600)	0.1074* (0.0227)	0.1142* (0.0185)	0.3395* (0.0207)	_	0.2646* (0.0095)
Rio Tinto	0.0236 (0.0159)	0.0854* (0.0198)	0.8326* (0.0893)	0.1159* (0.0267)	0.1304* (0.0290)	0.2950* (0.0587)	_	0.4037* (0.0331)

Table 5.5 (continued). GARCH/GJR Unexpected Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	α_1	α_2	β_1	γ_1	δ_v
Royal & Sun Alliance Ins.	0.0662* (0.0298)	0.0964* (0.0212)	0.0160 (0.0085)	0.0355* (0.0079)	_	0.9611* (0.0082)	_	0.0338* (0.0233)
Royal Bank of Scotland	0.0312 (0.0257)	0.0932* (0.0206)	0.9972* (0.0828)	0.1353* (0.0291)	0.0682* (0.0286)	0.4432* (0.0423)	_	0.3786* (0.0230)
Sainsbury	0.0065 (0.0149)	0.0572* (0.0153)	0.2607* (0.0341)	0.0283* (0.0053)	_	-0.0835* (0.0125)	_	0.7214* (0.0244)
Scottish & Newcastle	0.0260 (0.0196)	0.0678* (0.0215)	0.5747* (0.1073)	0.1800* (0.0264)	_	0.5022* (0.0528)	_	0.2202* (0.0358)
Standard Chartered	-0.0090 (0.0267)	0.0842* (0.0214)	1.3818* (0.1306)	0.1742* (0.0234)	_	0.4738* (0.0377)	_	0.4718* (0.0391)
Unilever	0.0355* (0.0082)	0.1010* (0.0189)	0.6054* (0.0218)	0.1699* (0.0113)	_	0.3035* (0.0041)	_	0.0986* (0.0036)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level. The mean equations for BAT Industries and RMC include a dummy variable term to remove the effect of one-off large outliers (BAT Industries 25.9 per cent return on 11/7/1989 and RMC 19.2 per cent return on 1/6/1998)

Table 5.6. GARCH/GJR Unexpected Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Asda	0.6141	2.3234	8.6772	0.6855	26.382	58.663*	0.6842	5.5052*	5.4899*
Associated British Foods	0.0024	9.1821	15.407	3.6388	6.8651	11.534	3.6360	1.3374	1.1508
BAA	1.9372	5.4839	7.8564	0.0113	2.4187	38.342*	0.0113	0.4839	3.9682*
BAT Industries	0.2817	17.146*	28.186*	0.0863	2.1929	11.489	0.0862	0.4397	1.1378
BOC	0.0231	3.6959	11.307	1.1249	4.8922	51.090*	1.1231	0.9864	5.9118*
BG	0.0367	8.4325	16.228	0.8789	4.3902	20.444*	0.8777	0.9153	2.1966*
BT	1.4769	7.5443	16.797	0.0101	2.7540	28.456*	0.0101	0.5418	2.8808*
Barclays	0.7482	4.1447	12.388	4.7056*	8.9770	43.044*	4.7050*	1.8397	4.6631*
Bass	0.9677	11.084	29.292*	1.7674	7.9894	53.615*	1.9694	1.7181	6.0927*
Blue Circle	0.1070	6.1445	12.660	0.2992	5.4260	29.334*	0.2686	1.0432	3.9737*
Boots	1.8918	4.1472	31.274*	1.9703	57.795*	101.24*	1.9759	10.707*	7.7317*
British Airways	0.1832	1.5038	13.906	0.0024	1.5678	23.654*	0.0024	0.3149	2.5521*
CGU	0.1222	7.1642	16.719	3.0683	6.1089	10.106	3.0651	1.2448	1.0208
Cadbury Schweppes	0.0408	10.119	22.930*	1.0993	1.9864	41.329*	1.1048	0.3887	3.8901*
Diageo	0.0455	10.871	24.943*	1.0894	3.0118	15.606	1.0896	0.6051	1.7341
EMI	0.3839	2.7538	15.958	0.0629	20.743*	89.247*	0.0628	4.1216*	9.3464*
Enterprise Oil	4.1018*	10.316	21.075*	0.0004	34.947*	63.199*	0.0004	6.7451*	5.3247*
General Electric	0.2451	8.9423	27.332*	5.3592*	11.001	39.795*	6.0292*	2.6328*	4.7568*
Glaxo Wellcome	0.4037	13.911*	30.098*	4.1829	29.714*	92.905*	4.1809*	6.4296*	8.7526*
ICI	0.1939	5.3712	9.7724	2.2251	15.561*	43.077*	2.2951	3.3451*	4.4991*
Ladbroke	1.1738	10.535	11.019*	2.0821	11.423*	72.437*	2.0804*	2.2131	6.7811*
Land Securities	0.2618	5.4618	14.522	9.0008*	20.650*	45.420*	9.0123*	3.7049*	3.8152*
Legal & General	0.0549	2.2938	14.715	0.0083	7.2202	28.791*	0.0083	1.3831	3.0166*
Marks & Spencer	0.2136	14.802*	33.109*	3.9802*	21.714*	74.110*	3.9775*	4.0310*	6.1527*
Natwest Bank	0.0890	13.750*	32.476*	0.0001	39.399*	87.396*	0.0001	7.8252*	7.5058*
Pearson	0.1519	9.9353	18.507*	1.3207	120.75*	257.00*	1.3247	24.619*	20.691*
Prudential	0.4772	15.261*	34.091*	0.0395	26.378*	61.684*	0.0394	4.9951*	5.1421*
RMC	0.0007	7.7363	12.933	1.1411	3.2393	33.568*	1.1392	0.6330	3.1682*
Rank Group	0.2796	3.8249	11.053	2.8306	33.417*	62.412*	2.8355	6.7158*	5.9716*
Reckitt & Colman	0.2249	5.8773	12.711	0.1401	22.326*	34.681*	0.1398	4.6013*	3.4130*
Reed International	0.5179	5.2076	5.6596	3.3042	25.952*	55.124*	3.3016	5.0844*	4.8906*

Table 5.6 (continued). GARCH/GJR Unexpected Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Reuters	3.6575	22.231*	25.126*	0.9320	8.4260	51.494*	0.9319	1.6514	5.1225*
Rio Tinto	0.1140	11.909*	21.097*	0.4192	26.612*	132.64*	0.4192	5.3777*	13.092*
Royal & Sun Alliance Ins.	0.6297	5.6465	11.367	0.0234	0.6188	6.0994	0.0233	0.1233	0.3061
Royal Bank of Scotland	0.6050	7.8885	16.272	0.0342	2.1342	17.639	0.0341	0.4192	1.8317
Sainsbury	1.8435	11.318*	18.924*	1.1090	36.136*	100.49*	1.1088	6.3097*	7.5067*
Scottish & Newcastle	0.0023	10.744	12.766	0.2689	0.7580	4.6662	0.2689	0.1495	0.4628
Standard Chartered	0.9790	3.4533	19.663*	0.0801	27.914*	72.543*	0.0800	5.6284*	6.3290*
Unilever	0.2395	5.5467	14.483	2.6712	20.773*	95.678*	2.6709	4.3882*	9.3880*

Notes: Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 5.7. CGARCH/ACGARCH Volume Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = q_t + \alpha(\epsilon^2_{t-1} - q_{t-1}) + \delta_s(D_{t-1}\epsilon^2_{t-1} - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \delta_{vs}V_t$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon^2_{t-1} - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero. V_t is the volume of trade in millions of shares.

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β	δ_{vs}
Asda	0.0415 (0.0251)	-0.0084 (0.0205)	0.9794* (0.3656)	0.9833* (0.0037)	0.0335* (0.0081)	-0.0298 (0.0250)	_	0.0926 (0.1955)	0.0956* (0.0425)
Associated British Foods	0.0201 (0.0161)	0.1196* (0.0223)	0.5444* (0.1104)	0.9815* (0.0082)	0.0301* (0.0067)	0.0711* (0.0246)	_	0.0418 (0.0529)	0.5915* (0.0684
BAA	0.0254 (0.0191)	0.0558* (0.0192)	0.5535* (0.0522)	0.9040* (0.0368)	0.0274* (0.0070)	0.1332* (0.0221)	_	-0.0215* (0.0034)	0.2778* (0.0227)
BG	0.0221 (0.0253)	0.0706* (0.0216)	1.5659* (0.4478)	0.9828* (0.0082)	0.0414* (0.0153)	0.0290 (0.0311)	_	0.6165* (0.1882)	0.0147* (0.0058)
BT	0.0073 (0.0124)	0.0743* (0.0185)	0.3667* (0.1721)	0.9714* (0.0128)	0.0265* (0.0060)	0.0104 (0.0161)	_	0.1353 (0.2319)	0.0840* (0.0073)
Barclays	0.0454* (0.0162)	0.0945* (0.0184)	0.8827* (0.1303)	0.9531* (0.0089)	0.0841* (0.0078)	-0.0019 (0.0223)	0.0850* (0.0400)	0.0979* (0.0269)	0.2274* (0.0156)
Bass	0.0054 (0.0186)	0.1047* (0.0196)	0.3635* (0.0980)	0.9897* (0.0029)	0.0203* (0.0037)	0.1064* (0.0259)	_	-0.0434* (0.0218)	0.3860* (0.0328)
Blue Circle	-0.0243 (0.0181)	0.1256* (0.0302)	3.2901 (1.9889)	0.9884* (0.0050)	0.0701* (0.0259)	0.1165* (0.0362)	_	0.1180 (0.0848)	0.5402* (0.0816)
Boots	0.0402 (0.0233)	0.0614* (0.0192)	0.6601* (0.0595)	0.9731* (0.0053)	0.0112* (0.0021)	0.0463* (0.0216)	_	-0.0113* (0.0020)	0.3966* (0.0421)
British Airways	0.0309 (0.0189)	0.0837* (0.0194)	0.6735* (0.1613)	0.9843* (0.0046)	0.0330* (0.0071)	0.0291 (0.0322)	0.0967* (0.0460)	0.1717* (0.0668)	0.2536* (0.0301)
CGU	-0.0068 (0.0221)	0.0648* (0.0186)	0.8625* (0.0949)	0.9533* (0.0082)	0.0264* (0.0049)	0.0311 (0.0222)	_	0.0340 (0.0665)	0.6472* (0.0484)
Cadbury Schweppes	0.0044 (0.0189)	0.0801* (0.0168)	0.4569* (0.0584)	0.9676* (0.0027)	0.0373* (0.0049)	0.0836* (0.0242)	-0.0915* (0.0229)	-0.0127* (0.0046)	0.1866* (0.0085)
Diageo	0.0180 (0.0133)	0.0641* (0.0197)	0.3766* (0.0746)	0.9865* (0.0038)	0.0160* (0.0029)	0.0767* (0.0230)	_	0.0072 (0.0144)	0.2076* (0.0152)
EMI	0.0177 (0.0131)	0.0677* (0.0185)	0.2966* (0.0844)	0.9877* (0.0038)	0.0165* (0.0035)	0.0583* (0.0203)	_	0.0329 (0.0685)	0.2523* (0.0344)
Enterprise Oil	-0.0638* (0.0199)	0.1119* (0.0197)	0.2561* (0.0439)	0.9865* (0.0019)	0.0021* (0.0005)	0.1485* (0.0283)	_	0.0371 (0.0217)	1.1959* (0.0969)
General Electric	-0.0080 (0.0077)	0.0626* (0.0172)	0.4449* (0.0997)	0.9824* (0.0063)	0.0231* (0.0052)	-0.0364* (0.0150)	0.0593* (0.0288)	0.0432* (0.0166)	0.1715* (0.0097)

Table 5.7 (continued). CGARCH/ACGARCH Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β	δ_{vs}
Glaxo Wellcome	0.0421* (0.0150)	0.0431* (0.0135)	0.7847* (0.0790)	0.8905* (0.0172)	0.0893* (0.0145)	-0.0542* (0.0172)	_	-0.0586* (0.0112)	0.2351* (0.0140)
ICI	-0.0265 (0.0157)	0.0868* (0.0189)	0.2714* (0.0544)	0.9784* (0.0044)	0.0199* (0.0031)	0.0433 (0.0256)	_	0.0030 (0.0719)	0.3016* (0.0307)
Ladbroke	-0.0132 (0.0219)	0.0474* (0.0197)	0.7498* (0.1756)	0.9816* (0.0032)	0.0358* (0.0047)	0.0620* (0.0236)	_	0.0279 (0.0272)	0.3560* (0.0324)
Land Securities	-0.0013 (0.0129)	0.0531* (0.0186)	1.3913* (0.6931)	0.9968* (0.0019)	0.0221* (0.0035)	0.0724* (0.0264)	_	-0.0052 (0.1670)	0.5413* (0.0465)
Legal & General	-0.0096 (0.0087)	0.0807* (0.0192)	2.7125 (1.4145)	0.9965* (0.0022)	0.0366* (0.0041)	0.0360 (0.0210)	_	0.0433* (0.0094)	0.0703* (0.0048)
Marks & Spencer	0.0090 (0.0172)	0.0747* (0.0184)	0.9190* (0.1077)	0.9751* (0.0058)	0.0426* (0.0075)	0.0860* (0.0169)	_	-0.2453* (0.0460)	0.1722* (0.0166)
Pearson	0.0269 (0.0151)	0.0612* (0.0190)	1.8456* (0.1504)	0.7478* (0.1531)	0.1049 (0.0609)	0.0584 (0.0652)	_	-0.0534 (0.1952)	0.0834 (0.1277)
Prudential	0.0224 (0.0156)	0.0561* (0.0172)	0.5001* (0.1125)	0.8751* (0.0058)	0.0350* (0.0058)	0.0266 (0.0226)	_	0.1964* (0.0290)	0.3533* (0.0229)
RMC	0.0200 (0.0147)	0.1187* (0.0200)	0.7955* (0.0807)	0.9336* (0.0238)	0.0444* (0.0129)	0.0341 (0.0223)	_	-0.0572* (0.0250)	2.0448* (0.3302)
Rank Group	-0.0031 (0.0207)	0.0706* (0.0187)	0.4995* (0.0715)	0.9724* (0.0054)	0.0238* (0.0043)	0.0941* (0.0207)	_	0.0074 (0.0131)	0.5498* (0.0379)
Reckitt & Colman	-0.0186 (0.0124)	0.1265* (0.0188)	0.3074* (0.0473)	0.9745* (0.0058)	0.0191* (0.0040)	0.0854* (0.0193)	_	0.0150 (0.0214)	0.1690* (0.0614)
Reed International	0.0241 (0.0198)	0.0820* (0.0198)	0.2896* (0.0560)	0.9312* (0.0275)	0.0252* (0.0065)	0.0704* (0.0205)	_	-0.0134 (0.0538)	0.4935* (0.0224)
Reuters	0.0418* (0.0193)	0.0989* (0.0173)	0.2792* (0.0463)	0.9802* (0.0032)	0.0094* (0.0023)	0.0536* (0.0142)	_	-0.0189* (0.0081)	0.4421* (0.0194)
Rio Tinto	0.0175 (0.0133)	0.0836* (0.0190)	2.6886* (1.3178)	0.9950* (0.0030)	0.0584* (0.0079)	0.0745* (0.0228)	_	0.2022* (0.0537)	0.2671* (0.0306)
Royal Bank of Scotland	0.0046 (0.0243)	0.0845* (0.202)	1.1828* (0.1902)	0.9710* (0.0072)	0.0452* (0.0094)	0.0476* (0.0181)	_	0.0622 (0.0442)	0.5088* (0.0446)
Sainsbury	0.0174 (0.0100)	0.1012* (0.0167)	0.4280* (0.0676)	0.9868* (0.0041)	0.0099* (0.0023)	-0.0036 (0.0140)	_	0.0232 (0.0426)	0.4196* (0.0294)
Standard Chartered	0.0210 (0.0296)	0.0814* (0.0204)	0.8561* (0.1276)	0.9867* (0.0023)	0.0107* (0.0015)	0.0946* (0.0222)	_	-0.0001 (0.0124)	0.3864* (0.0396)
Unilever	0.0420* (0.0160)	0.1164* (0.0483)	0.5067* (0.1584)	0.9933* (0.0026)	0.0364* (0.0057)	0.0414* (0.0181)	_	0.0989 (0.0829)	0.0558* (0.0063)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 5.8. CGARCH/ACGARCH Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Asda	2.8900	6.0910	15.708	10.958*	12.988*	15.095	10.978*	2.4899*	1.4885
Associated British Foods	0.1628	10.265	16.342	0.0044	4.6279	9.7915	0.0044	0.8958	0.9091
BAA	2.7773	6.8762	8.7664	0.0012	6.8533	32.024*	0.0012	1.3558	2.9712*
BG	0.1940	3.3156	9.7651	0.4949	8.9974	11.889	0.4940	1.7904	1.2050
BT	1.1406	4.7294	12.183	0.6188	1.1039	3.2887	0.6178	0.2146	0.3295
Barclays	0.3809	3.1792	12.038	1.4679	4.1876	10.299	1.4661	0.8262	1.0293
Bass	2.0043	12.491*	24.655*	0.1070	2.1107	21.398*	0.1087	0.4308	2.0899*
Blue Circle	0.6634	7.6394	13.581	0.4450	7.6057	9.4487	0.4441	1.4657	1.0542
Boots	0.6300	2.7737	26.612*	1.0203	21.135*	30.116*	1.0187	3.9694*	2.6039*
British Airways	0.3975	2.3796	13.147	1.2088	5.2392	6.5176	1.2069	1.0785	0.6826
CGU	0.0399	8.0505	21.345*	3.3190	11.862*	23.283*	3.3166	2.1610	1.9434
Cadbury Schweppes	0.3606	10.632	21.911*	0.0664	0.7992	4.7183	0.0666	0.1616	0.4710
Diageo	0.3987	10.232	21.603*	0.1228	8.8004	13.782	0.1228	1.7128	1.2479
EMI	1.3111	6.1557	16.122	0.4285	4.2233	22.570*	0.4279	0.8663	2.2819*
Enterprise Oil	0.1621	5.5239	13.937	0.0552	23.944*	28.760*	0.0551	4.7676*	2.7545*
General Electric	0.4089	8.5853	25.919*	0.2332	8.4892	15.636	0.2437	1.8473	1.5851
Glaxo Wellcome	0.8053	13.709*	26.575*	0.6730	2.4449	13.997	0.6718	0.5065	1.3778
ICI	0.3350	6.3534	8.8517	0.1060	0.6048	5.5951	0.1063	0.1175	0.5656
Ladbroke	0.1193	8.5996	9.9433	0.2056	6.3753	9.0452	0.2054	1.2925	0.9138
Land Securities	0.4562	3.2834	10.435	0.0016	2.8709	8.2273	0.0016	0.5631	0.8025
Legal & General	0.0041	4.4905	16.020	2.4952	4.9024	8.1433	2.4921	0.9593	0.8102
Marks & Spencer	0.0676	10.535	27.081*	0.0037	2.5747	4.5618	0.0037	0.5174	0.4553
Pearson	0.0001	7.9861	12.685*	0.9508	5.6691	28.188*	0.9513	1.1779	3.0073*
Prudential	1.0013	14.610*	27.641*	0.2626	4.5547	5.7387	0.2621	0.8892	0.5562
RMC	0.2669	6.0186	10.533	1.8174	2.0065	6.6024	1.8148	0.4043	0.6592
Rank Group	0.2879	5.2339	9.8209	0.1958	6.6074	12.657	0.1957	1.3230	1.2270
Reckitt & Colman	0.1134	6.5261	15.753	0.1242	8.2997	12.475	0.1240	1.6725	1.2799
Reed International	0.7002	4.6350	4.9889	0.0873	10.933	16.560	0.0871	2.2266	1.6390
Reuters	4.3981*	24.439*	28.434*	0.8270	19.030*	33.959*	0.8297	3.5353*	2.9921*
Rio Tinto	1.3329	11.062	14.862	1.3698	2.9272	9.4869	1.3681	0.5789	1.0133
Royal Bank of Scotland	0.5611	8.3788	16.156	0.0418	3.3798	4.7675	0.0417	0.6682	0.4697
Sainsbury	0.0362	5.5118	14.459	0.6772	4.3573	21.385*	0.6762	0.8710	2.0200*
Standard Chartered	2.7089	5.5762	20.408*	0.0007	57.107*	79.223*	0.0001	10.967*	6.7059*
Unilever	0.5537	3.8053	10.839	1.4176	8.4768	11.114	1.4162	1.6580	1.1471

Notes: Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 5.9. CGARCH/ACGARCH Lagged Volume Model
Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t,\quad h_t = q_t + \alpha(\epsilon^2_{t-1} - q_{t-1}) + \delta_s(D_{t-1}\epsilon^2_{t-1} - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \delta_{vs}V_{t-1}$$
$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon^2_{t-1} - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero. V_{t-1} is the volume of trade in millions of shares for period t - 1.

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β	δ_{vs}
Asda	0.0755* (0.0328)	0.0109 (0.0241)	5.6015 (5.5342)	0.9928* (0.0070)	0.0487* (0.0166)	0.1766 (0.1298)	_	0.0514 (0.0966)	0.0615* (0.0282)
Associated British Foods	0.0503* (0.0186)	0.1372* (0.0228)	1.5458* (0.6847)	0.9965* (0.0044)	0.0225* (0.0075)	0.1399 (0.0303)	_	0.2189 (0.1769)	-0.0654* (0.0243)
BAA	0.0521* (0.0213)	0.1021 (0.0215)	1.5335 (0.2494)	0.9926* (0.0045)	0.0188* (0.0086)	0.1739* (0.0376)	_	0.2723* (0.1171)	0.0254 (0.0204)
BG	0.0221 (0.0253)	0.0706* (0.0216)	1.5659* (0.4478)	0.9828* (0.0082)	0.0414* (0.0153)	0.0290 (0.0311)	_	0.6165* (0.1882)	0.0147* (0.0058)
BT	0.0357 (0.0224)	0.1104* (0.0214)	1.3525* (0.2456)	0.9843* (0.0113)	0.0324* (0.0102)	0.0599 (0.0363)	_	-0.0363 (0.2008)	0.0453* (0.0174)
Barclays	0.0496* (0.0170)	0.1112* (0.0170)	2.5006* (0.6250)	0.9822* (0.0088)	0.0612* (0.0127)	-0.0089 (0.0359)	0.1627* (0.0672)	0.0593 (0.1442)	0.0722* (0.320)
Bass	0.0177 (0.0214)	0.1252* (0.0220)	1.8740 (1.0513)	0.9977* (0.0037)	0.0147* (0.0061)	0.1454* (0.0453)	_	0.1176 (0.1872)	0.0252 (0.0456)
Blue Circle	0.0101 (0.0286)	0.1153* (0.0249)	3.4267* (1.1260)	0.9903* (0.0054)	0.0373* (0.0127)	0.0853* (0.0392)	_	0.5974* (0.1626)	-0.0083 (0.0386)
Boots	0.0597* (0.0243)	0.0802* (0.0198)	1.8613* (0.3000)	0.9909* (0.0040)	0.0235* (0.0067)	0.0906* (0.0377)	-0.0960* (0.0430)	0.7257* (0.1262)	-0.0027 (0.0047)
British Airways	0.0532 (0.0276)	0.0896* (0.0209)	2.3006* (0.5764)	0.9947* (0.0032)	0.0191* (0.0066)	-0.0063 (0.0260)	0.1803* (0.0515)	0.5147* (0.1234)	0.0478 (0.0246)
CGU	0.0356 (0.0253)	0.0783* (0.0210)	1.9873* (0.4056)	0.9888* (0.0058)	0.0396* (0.0094)	0.0619* (0.0286)	_	-0.0573 (0.0437)	0.1781* (0.0625)
Cadbury Schweppes	0.0342 (0.0239)	0.0963* (0.0193)	2.0558* (0.2157)	0.9737* (0.0096)	0.0320* (0.0144)	0.1068* (0.0338)	-0.1007* (0.0372)	0.7381* (0.0775)	-0.0093* (0.0023)
Diageo	0.0620* (0.0240)	0.1023* (0.0231)	2.3932* (0.9043)	0.9933* (0.0062)	0.0245* (0.0116)	0.0798* (0.0272)	_	0.6573* (0.1461)	0.0001 (0.0057)
EMI	0.0425* (0.0216)	0.1110* (0.0212)	1.8454 (1.3976)	0.9971* (0.0055)	0.0189* (0.0054)	0.0356 (0.0284)	_	0.4180 (0.3080)	0.0438 (0.0332)
Enterprise Oil	0.0384* (0.0087)	0.1317* (0.0295)	2.6670* (0.3187)	0.6162 (0.7907)	0.0392 (0.2012)	0.0572 (0.2027)	_	-0.1934 (1.7548)	-0.0183* (0.0025)
General Electric	0.0373 (0.0254)	0.0894* (0.0193)	1.6930* (0.2317)	0.9742* (0.0117)	0.0456* (0.0111)	-0.0850* (0.0251)	_	-0.2466 (0.1373)	0.0760* (0.0188)

Table 5.9 (continued). CGARCH/ACGARCH Lagged Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β	δ_{vs}
Glaxo Wellcome	0.0762* (0.0281)	0.0687* (0.0217)	4.5531* (1.5950)	0.9970* (0.0032)	0.0048 (0.0096)	0.0455* (0.0136)	_	0.9284* (0.0207)	-0.0084 (0.0043)
ICI	0.0159 (0.0237)	0.1176* (0.0211)	1.7665* (0.8082)	0.9930* (0.0076)	0.0259* (0.0075)	0.0625* (0.0385)	_	0.1034 (0.2536)	0.0980* (0.0428)
Ladbroke	0.0267* (0.0123)	0.0468 (0.0251)	3.7257* (1.1035)	0.9836* (0.0068)	0.0636* (0.0168)	0.0453 (0.0372)	_	-0.4659* (0.1214)	0.1486* (0.0451)
Land Securities	0.0283 (0.0188)	0.0797* (0.0201)	1.2394* (0.1992)	0.9852* (0.0059)	0.0445* (0.0093)	0.0259 (0.0275)	_	-0.3364 (0.1900)	0.1537* (0.0475)
Legal & General	0.0544* (0.0258)	0.1030* (0.0221)	2.2533* (0.6205)	0.9937* (0.0036)	0.0264* (0.0074)	0.0743* (0.0312)	_	0.4253* (0.1828)	0.0123 (0.0064)
Marks & Spencer	0.0159 (0.0245)	0.0875* (0.0213)	1.8259* (0.2479)	0.9837* (0.0070)	0.0324* (0.0083)	0.0901* (0.0355)	_	-0.1334 (0.2118)	0.0350 (0.0307)
Pearson	0.0390 (0.0250)	0.0686* (0.0215)	1.8468* (0.2040)	0.9585* (0.0133)	0.0526* (0.0153)	0.0355 (0.0286)	_	-0.0342 (0.0345)	0.1330* (0.0632)
Prudential	0.0614* (0.0278)	0.0780* (0.0213)	1.8231* (0.4108)	0.9930* (0.0045)	0.0185* (0.0070)	0.0940* (0.0353)	_	0.3423* (0.1388)	0.1131* (0.0368)
RMC	0.0257 (0.0232)	0.1453* (0.0232)	2.9505 (3.8134)	0.9977* (0.0061)	0.0237* (0.0063)	0.0674* (0.0315)	_	0.5420* (0.1952)	-0.0455 (0.0870)
Rank Group	0.0176 (0.0270)	0.0794* (0.0227)	2.3310* (0.4703)	0.9675* (0.0141)	0.0711* (0.0242)	0.0840* (0.0417)	_	0.0295 (0.2426)	0.1462* (0.0674)
Reckitt & Colman	0.0316 (0.0198)	0.1405* (0.0219)	1.3022* (0.1673)	0.9658* (0.0137)	0.0504* (0.0123)	0.1020* (0.0244)	_	-0.5141* (0.1495)	0.1150 (0.0640)
Reed International	0.0307 (0.0240)	0.1065* (0.0217)	2.1319* (0.6860)	0.9895* (0.0069)	0.0415* (0.0120)	0.1120* (0.0315)	_	-0.0759 (0.1875)	0.0090 (0.0406)
Reuters	0.0725* (0.0271)	0.1680* (0.0247)	2.3846* (0.5991)	0.9875* (0.0051)	0.0295* (0.0114)	0.1627* (0.0746)	_	0.1796 (0.1301)	0.0523 (0.0366)
Rio Tinto	0.0403 (0.0233)	0.0986* (0.0211)	1.7122* (0.4212)	0.9891* (0.0050)	0.0422* (0.0093)	0.0627 (0.0388)	_	0.1242 (0.2447)	0.1327* (0.0430)
Royal Bank of Scotland	0.0513 (0.0286)	0.1080* (0.0223)	2.8909* (0.8659)	0.9942* (0.0045)	0.0244* (0.0066)	0.0943* (0.0294)	_	0.1638 (0.2161)	0.0950* (0.0476)
Sainsbury	0.0329 (0.0253)	0.1257* (0.0207)	1.6280* (0.2541)	0.9842* (0.0078)	0.0263* (0.0080)	0.0421 (0.0292)	_	-0.1786* (0.0430)	0.1583* (0.0470)
Standard Chartered	0.0927* (0.0297)	0.1055* (0.0225)	3.7929* (1.3816)	0.9905* (0.0049)	0.0497* (0.0113)	0.0920* (0.0250)	_	0.4610* (0.0764)	0.0851* (0.0221)
Unilever	0.0456* (0.0193)	0.1399* (0.0206)	1.0908* (0.2271)	0.9933* (0.0041)	0.0245* (0.0062)	0.0671* (0.0268)	_	0.4443 (0.2654)	0.0062 (0.0074)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 5.10. CGARCH/ACGARCH Lagged Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Asda	1.7675	3.9479	12.347	0.1113	1.2040	1.8148	0.1111	0.2421	0.1762
Associated British Foods	0.0197	9.5603	16.374	0.2621	2.4513	6.8115	0.2616	0.4763	0.6281
BAA	0.3233	4.2766	6.7146	0.0272	4.3403	6.7779	0.0271	0.8661	0.6930
BG	0.1940	3.3156	9.7651	0.4949	8.9974	11.889	0.4940	1.7904	1.2050
BT	0.1195	4.4031	10.650	0.0031	1.4698	7.6083	0.0031	0.2951	0.7577
Barclays	0.2093	2.6443	10.668	0.4892	1.0485	5.0811	0.4884	0.2047	0.5001
Bass	1.2339	9.3063	19.585*	0.0100	0.6248	7.8611	0.0100	0.1276	0.7742
Blue Circle	0.0200	5.5118	14.094	0.0907	3.4854	6.1222	0.0905	0.7021	0.7298
Boots	0.0626	2.1850	25.592*	0.0871	6.1504	9.2793	0.0869	1.1761	0.9234
British Airways	0.4315	1.6136	11.091	0.1849	1.5030	2.9113	0.1845	0.3030	0.2950
CGU	0.3518	6.6024	17.561	0.0567	2.9577	4.5833	0.0566	0.5918	0.4602
Cadbury Schweppes	0.0261	7.5893	19.458*	0.0364	3.5046	6.9288	0.0364	0.7043	0.6898
Diageo	0.2184	6.5987	19.177*	0.0919	0.8355	1.1201	0.0917	0.1685	0.1115
EMI	0.0002	4.4484	11.507	0.0079	0.3540	4.7006	0.0079	0.0707	0.4619
Enterprise Oil	0.7074	3.6960	17.965	0.0825	1.2927	1.8610	0.0823	0.2560	0.1791
General Electric	0.0351	5.1407	19.496*	0.0357	2.8424	6.4349	0.0363	0.6094	0.7132
Glaxo Wellcome	0.7311	8.9113	16.324	0.1398	1.5011	4.6018	0.1395	0.2943	0.4504
ICI	0.1960	5.6037	7.2331	0.1151	0.2760	4.2486	0.1149	0.0543	0.4160
Ladbroke	0.2030	6.8354	8.8491	0.0779	4.6738	7.9765	0.0778	0.9348	0.8000
Land Securities	0.0454	3.2074	7.2641	0.5036	0.9535	2.6020	0.5037	0.1918	0.2624
Legal & General	0.2265	2.8076	14.886	0.0104	2.1345	5.7984	0.0104	0.4217	0.5776
Marks & Spencer	0.0181	8.2328	21.508*	0.1633	1.7072	3.1437	0.1629	0.3419	0.3204
Pearson	0.0527	7.3360	11.152	0.1541	1.3714	5.8832	0.1539	0.2763	0.6263
Prudential	0.2326	14.618*	26.993*	0.2413	1.1834	2.6124	0.2408	0.2320	0.2551
RMC	1.2061	6.4484	9.8771	2.2444	2.5654	3.9011	2.2414	0.5133	0.3851
Rank Group	0.0002	3.9585	11.666	0.2662	11.747*	12.782	0.2658	2.3129*	1.2386
Reckitt & Colman	0.0026	5.8552	10.889	0.3493	0.7443	5.1702	0.3486	0.1503	0.5154
Reed International	0.2859	3.0381	3.1715	0.3075	0.4992	2.5403	0.3069	0.0950	0.2530
Reuters	0.3406	12.001*	14.453	0.0002	1.0357	4.5515	0.0002	0.2085	0.4545
Rio Tinto	0.5440	8.8042	11.631	0.0527	3.2831	11.102	0.0526	0.6559	1.1792
Royal Bank of Scotland	0.0560	6.4315	12.948	0.0272	1.1872	2.9425	0.0272	0.2369	0.2853
Sainsbury	0.0984	2.1679	7.9750	0.1288	1.3398	4.3036	0.1286	0.2698	0.4221
Standard Chartered	0.9828	3.9451	19.569*	1.6386	2.8622	6.3124	1.6368	0.5726	0.6389
Unilever	0.0529	2.5173	7.6474	0.5550	1.0680	3.1226	0.5541	0.2101	0.3278

Notes: Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 5.11. CGARCH/ACGARCH Unexpected Volume Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \delta_{vs}V_t^*$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero. V_t^* is the innovation in the volume of trade, that is, the residuals of a fitted ARMA model for volume of trade.

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β	δ_{vs}
Asda	0.0368 (0.0236)	-0.0040 (0.0209)	1.8294* (0.5433)	0.9816* (0.0042)	0.0346* (0.0100)	-0.0330 (0.0245)	_	0.4140* (0.1180)	0.0874* (0.0306)
Associated British Foods	0.0324 (0.0181)	0.1353* (0.0222)	1.0135* (0.1583)	0.9937* (0.0043)	0.0166* (0.0047)	0.1385* (0.0270)	_	0.1282* (0.0430)	0.4451* (0.0460)
BAA	0.0427* (0.0202)	0.0832* (0.0193)	1.3033* (0.0691)	0.9664* (0.0201)	0.0112 (0.0065)	0.1539* (0.0226)	_	0.0951* (0.0210)	0.1403* (0.0124)
BG	0.0099 (0.0091)	0.0665* (0.0193)	1.6393* (0.1543)	0.9728* (0.0067)	0.0439* (0.0093)	0.0094 (0.0212)	_	0.6194* (0.0888)	0.0406* (0.0028)
BT	0.0160 (0.0163)	0.0897* (0.0192)	1.1647* (0.0957)	0.9775* (0.0066)	0.0275* (0.0053)	0.0059 (0.0167)	_	0.6788* (0.0932)	0.0547* (0.0034)
Barclays	0.0437 (0.0244)	0.0887* (0.0201)	1.9046* (0.1640)	0.9655* (0.0083)	0.0411* (0.0107)	0.0472 (0.0305)	0.1436* (0.0526)	0.1930 (0.1106)	0.1650* (0.0463)
Bass	-0.0006 (0.0006)	0.1126* (0.0195)	0.9787* (0.1699)	0.9927* (0.0025)	0.0194* (0.0016)	0.1163* (0.0255)	_	0.1807* (0.0223)	0.3235* (0.0167)
Blue Circle	-0.0369 (0.0238)	0.1034* (0.0252)	2.4437* (0.3177)	0.9348* (0.0186)	0.0985* (0.0427)	0.0399 (0.0282)	_	0.3198* (0.1032)	0.4381* (0.0702)
Boots	0.0356 (0.0199)	0.0578* (0.0189)	1.4553* (0.0821)	0.9848* (0.0032)	0.0065* (0.0015)	0.0480* (0.0200)	_	0.0365* (0.0009)	0.4919* (0.0317)
British Airways	0.0353 (0.0201)	0.0890* (0.0199)	1.8294* (0.2631)	0.9905* (0.0034)	0.0257* (0.0069)	0.0744* (0.0185)	_	0.6214* (0.0465)	0.1963* (0.0230)
CGU	0.0130 (0.0247)	0.0756* (0.0200)	1.7982* (0.1849)	0.9813* (0.0073)	0.0396* (0.0089)	0.0455 (0.0308)	_	0.0877 (0.2801)	0.2551* (0.0527)
Cadbury Schweppes	0.0182 (0.0213)	0.0982* (0.0173)	1.3449* (0.1227)	0.9704* (0.0072)	0.0511* (0.0077)	0.0948* (0.0272)	-0.1276* (0.0353)	0.0251 (0.0242)	0.1040* (0.0035)
Diageo	0.0379 (0.0230)	0.0966* (0.0259)	1.6501* (0.2085)	0.9942* (0.0029)	0.0081* (0.0028)	0.1764* (0.0388)	_	0.2430* (0.1049)	0.1286* (0.0247)
EMI	0.0192 (0.0136)	0.0778* (0.0192)	0.9975* (0.2072)	0.9918* (0.0037)	0.0175* (0.0039)	0.0464* (0.0184)	_	0.5718* (0.0664)	0.1702* (0.0230)
Enterprise Oil	-0.0671* (0.0181)	0.1063* (0.0195)	2.3537* (0.1259)	0.9887* (0.0007)	0.0019* (0.0003)	0.1396* (0.0277)	_	0.0336* (0.0112)	1.2494* (0.0836)
General Electric	0.0109 (0.0099)	0.0545* (0.0179)	1.4314* (0.1407)	0.9897* (0.0032)	0.0157* (0.0038)	0.0324* (0.0140)	_	0.5086* (0.0382)	0.1347* (0.0079)

Table 5.11 (continued). CGARCH/ACGARCH Unexpected Volume Model Conditional Mean and Variance Specifications

Stock/Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β	δ_{vs}
Glaxo Wellcome	0.0449* (0.0158)	0.0446* (0.0140)	1.7816* (0.1041)	0.8423* (0.0276)	0.1161* (0.0250)	-0.0811* (0.0296)	_	0.4373* (0.0511)	0.2084* (0.0140)
ICI	-0.0181* (0.0136)	0.0867* (0.0193)	0.8158* (0.1604)	0.9864* (0.0042)	0.0174* (0.0035)	0.0221 (0.0195)	_	0.5508* (0.0816)	0.1770* (0.0246)
Ladbroke	-0.0285 (0.0217)	0.0466* (0.0198)	2.2698* (0.1962)	0.9770* (0.0021)	0.0308* (0.0032)	0.0604* (0.0208)	_	0.2786* (0.0271)	0.3618* (0.0175)
Land Securities	0.0063 (0.0149)	0.0531* (0.0185)	0.9237* (0.0785)	0.9812* (0.0044)	0.0285* (0.0038)	0.0424* (0.0199)	_	0.4289* (0.0563)	0.4135* (0.0285)
Legal & General	0.0121 (0.0098)	0.0893* (0.0197)	4.2702 (4.4138)	0.9981* (0.0029)	0.0437* (0.0057)	0.0453* (0.0220)	_	0.3183* (0.0616)	0.0473* (0.0026)
Marks & Spencer	0.0165 (0.0127)	0.0666* (0.0188)	1.4571* (0.0798)	0.9295* (0.0184)	0.0418* (0.0118)	0.0654* (0.0227)	_	0.3521* (0.0234)	0.2124* (0.0118)
Pearson	0.0202 (0.0306)	0.0646* (0.0206)	1.6568* (0.0966)	0.8724* (0.0537)	0.0714* (0.0271)	0.0542 (0.0356)	_	0.1027* (0.0512)	0.1872* (0.0617)
Prudential	0.0214 (0.0171)	0.0649* (0.0176)	1.8857* (0.3356)	0.9868* (0.0050)	0.0532* (0.0083)	0.0347 (0.0219)	_	0.4603* (0.0481)	0.2360* (0.0222)
RMC	0.0118 (0.0221)	0.1183* (0.0200)	1.6693* (0.1764)	0.9300* (0.0781)	0.0248 (0.0189)	0.0837* (0.0307)	_	0.1829* (0.0510)	1.8392* (0.3512)
Rank Group	-0.0176 (0.0171)	0.0510* (0.0182)	1.9693* (0.1262)	0.9742* (0.0087)	0.0232* (0.0043)	0.0821* (0.0205)	_	0.1512* (0.0255)	0.5328* (0.0192)
Reckitt & Colman	-0.0135 (0.0183)	0.1262* (0.0198)	1.1127* (0.1015)	0.9893* (0.0060)	0.0127* (0.0046)	0.0941* (0.0229)	_	0.1761* (0.0540)	0.6467* (0.0501)
Reed International	0.0500* (0.0194)	0.0979* (0.0202)	1.2030* (0.1303)	0.9897* (0.0024)	0.0077* (0.0023)	0.1245* (0.0244)	_	0.5106* (0.0306)	0.1894* (0.0206)
Reuters	0.0618* (0.0226)	0.1088* (0.0189)	1.6491* (0.1183)	0.9878* (0.0021)	0.0132* (0.0032)	0.0410* (0.0152)	_	0.5106* (0.0350)	0.2789* (0.0120)
Rio Tinto	0.0252 (0.0160)	0.0888* (0.0195)	1.3781* (0.1950)	0.9829* (0.0049)	0.0560* (0.0097)	0.0504* (0.0225)	_	0.5184* (0.0716)	0.2229* (0.0284)
Royal Bank of Scotland	0.0094 (0.0089)	0.0844* (0.0211)	2.3683* (0.3042)	0.9864* (0.0049)	0.0345* (0.0068)	0.0760* (0.0223)	_	0.2517* (0.0861)	0.3482* (0.0232)
Sainsbury	0.0282 (0.0223)	0.1009* (0.0186)	1.4539* (0.0985)	0.9874* (0.0052)	0.0102* (0.0030)	0.0146 (0.0150)	_	0.3956* (0.0350)	0.2155* (0.0121)
Standard Chartered	0.0404 (0.0279)	0.0696* (0.0204)	2.7840* (0.1825)	0.9299* (0.0341)	0.0276 (0.0147)	0.1225* (0.0321)	_	0.1193 (0.0788)	0.1528* (0.0410)
Unilever	0.0359* (0.0154)	0.1222* (0.0186)	0.8050* (0.1302)	0.9902* (0.0032)	0.0312* (0.0060)	0.0414* (0.0204)	_	0.4045* (0.0514)	0.0550* (0.0072)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 5.12. CGARCH/ACGARCH Unexpected Volume Model Residual Diagnostics

Stock/Index	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Asda	2.1954	5.4427	14.619	11.472*	14.612*	16.456	11.495*	2.7480*	1.5931
Associated British Foods	0.0799	10.962	17.365	0.8859	4.4501	12.188	0.8843	0.8343	1.1075
BAA	0.7458	4.7681	6.7127	0.0269	5.4513	23.769*	0.0270	1.1276	2.3255*
BG	0.0313	6.0437	12.565	0.0092	1.2407	6.1517	0.0092	0.2497	0.6207
BT	0.4304	4.9430	12.670	1.8306	3.4844	5.9645	1.8287	0.6958	0.5927
Barclays	0.8357	4.6014	14.338	0.5915	14.807*	27.589*	0.5909	3.0259*	2.6655*
Bass	1.3631	11.119*	23.219*	0.0539	1.0521	17.357	0.0548	0.2153	1.7760
Blue Circle	0.0473	7.0888	12.559	0.0057	3.9007	6.1442	0.0056	0.7750	0.7344
Boots	0.0951	3.2768	26.805*	1.2157	25.344*	38.785*	1.2138	4.7048*	3.2322*
British Airways	0.1946	2.0881	12.735	0.2786	2.4797	4.0513	0.2781	0.5030	0.4131
CGU	0.1125	6.5729	19.493*	1.4617	5.8868	7.0545	1.4594	1.1064	0.6597
Cadbury Schweppes	0.0042	9.1552	19.948*	0.0051	2.4574	3.9532	0.0051	0.4915	0.3858
Diageo	0.1911	10.585	22.966*	0.6125	3.1320	11.870	0.6127	0.6330	1.1481
EMI	0.6393	5.3744	14.289*	0.1292	1.0746	12.869	0.1290	0.2133	1.3038
Enterprise Oil	0.3083	5.7806	13.991	0.0079	25.629*	30.594*	0.0079	5.0660*	2.9218*
General Electric	1.4879	9.0456	27.637*	2.7732	12.079*	23.798*	2.9239	2.6974*	2.5113*
Glaxo Wellcome	0.6041	12.382*	25.545*	0.8150	2.2648	13.981	0.8136	0.4646	1.3842
ICI	0.9506	6.6429	8.6208	0.3187	0.8388	5.5477	0.9506	0.1662	0.5697
Ladbroke	0.0329	8.7254	10.105	0.7615	4.6297	7.8086	0.7609	0.9255	0.7859
Land Securities	0.4307	3.9937	11.298	0.3578	1.0456	4.9947	0.3572	0.2108	0.4915
Legal & General	0.0029	3.7683	15.878	0.6551	2.8975	6.0313	0.6540	0.5992	0.6091
Marks & Spencer	0.2203	11.346*	29.067*	0.0147	3.7161	8.2395	0.0147	0.7288	0.7661
Pearson	0.0005	7.5069	11.546	0.8469	3.7361	14.219	0.8474	0.7778	1.4997
Prudential	0.7636	14.679*	27.208*	0.1817	1.5321	2.6646	0.1813	0.3031	0.2421
RMC	0.2316	6.4848	11.612	0.5531	1.4505	11.627	0.5520	0.2847	1.1282
Rank Group	1.2331	3.3726	11.734	1.2069	9.1085	19.204*	1.2068	1.8141	1.8393
Reckitt & Colman	0.4151	6.5133	14.418	1.0451	12.720*	16.945	1.0433	2.6054*	1.7456
Reed International	0.7022	3.7671	4.3287	0.1138	4.7635	10.371	0.1136	0.9482	1.0522
Reuters	4.0251*	22.481*	25.609*	2.8989	7.0521	16.086	2.9029	1.3690	1.5173
Rio Tinto	0.9215	10.346	14.566	0.7424	1.9898	8.6030	0.7413	0.3972	0.8694
Royal Bank of Scotland	0.6684	9.1169	18.177	0.0960	2.2035	3.9448	0.0958	0.4294	0.3691
Sainsbury	0.1496	3.5672	11.478	0.4168	2.1192	18.797*	0.4161	0.4252	1.7847
Standard Chartered	4.0806*	6.4380	22.686*	0.2016	32.726*	53.226*	0.2014	6.6720*	4.8543*
Unilever	0.1960	3.3234	9.7029	1.4981	4.9192	7.8210	1.4966	0.9540	0.8229

Notes: Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Appendix 5

Table 6.1. Stochastic Volatility Conditional Mean and Variance Specifications

The following mean and variance specifications are used:

$$\ln(y_t^2) = \Lambda + h_t + \xi_t, \quad h_{t+1} = \Phi h_t + \eta_t$$

where $\Lambda = \ln(k^2) + E_t[\ln(\epsilon_t^2)]$ and $\ln(k^2) = \left(\frac{\delta}{1 - \Phi}\right)$.

Stock/Index	Λ	σ_ξ	Φ	σ_η	k^2
FTSE 100	-1.8366* (0.1460)	2.2840* (1.0000)	0.9913* (0.0015)	0.0661* (0.0020)	0.6321
Asda	-1.1702* (0.1196)	3.7710* (1.0000)	0.9402* (0.0211)	0.3037* (0.0162)	3.8724
Associated British Foods	-1.5173* (0.3386)	2.3695* (1.0000)	0.9963* (0.0004)	0.0710* (0.0019)	1.2563
BAA	-1.1810* (0.0750)	2.1340* (1.0000)	0.8654* (0.0745)	0.4495* (0.0637)	0.1493
BAT Industries	-0.8096* (0.0884)	2.3348* (1.0000)	0.9700* (0.0094)	0.1223* (0.0052)	2.1620
BOC	-1.2267* (0.2420)	2.5111* (1.0000)	0.9946* (0.0010)	0.0718* (0.0020)	1.5238
BG	-0.9665* (0.0578)	2.2495* (1.0000)	0.5467* (0.1954)	0.9327* (0.1829)	1.3305
BT	-1.0493* (0.0796)	2.2267* (1.0000)	0.9365* (0.0265)	0.2269* (0.0164)	1.4395
Barclays	-0.7560* (0.0855)	2.2576* (1.0000)	0.9091* (0.0455)	0.3565* (0.0387)	1.8802
Bass	-1.1513* (0.0574)	2.1772* (1.0000)	0.5974* (0.1822)	0.8479* (0.1652)	1.0474
Blue Circle	-0.9395* (0.1061)	3.2081* (1.0000)	0.9444* (0.0199)	0.2561* (0.0140)	2.6025
Boots	-0.9599* (0.0548)	2.2291* (1.0000)	0.7218* (0.0992)	0.5124* (0.0506)	1.4802
British Airways	-0.7173* (0.0745)	2.3967* (1.0000)	0.8541* (0.0718)	0.4550* (0.0529)	2.1073

Table 6.1 (continued). Stochastic Volatility Conditional Mean and Variance Specifications

Stock/Index	Λ	σ_ξ	Φ	σ_η	k^2
CGU	-0.7567* (0.2480)	2.4218* (1.0000)	0.9968* (0.0003)	0.0446* (0.0009)	2.2588
Cadbury Schweppes	-1.0439* (0.0534)	2.0842* (1.0000)	0.4541 (0.2361)	1.0364* (0.2408)	1.0602
Diageo	-0.9757* (0.2093)	2.2932* (1.0000)	0.9940* (0.0009)	0.0678* (0.0020)	1.8998
EMI	-1.2752* (0.0762)	2.4004* (1.0000)	0.9003* (0.0429)	0.3222* (0.0270)	1.3593
Enterprise Oil	-1.2008* (0.0792)	2.7441* (1.0000)	0.7066* (0.1545)	0.9255* (0.1803)	1.4444
General Electric	-1.0069* (0.0734)	2.4937* (1.0000)	0.9326* (0.0225)	0.2006* (0.0102)	1.7975
Glaxo Wellcome	-0.5620* (0.2578)	2.3471* (1.0000)	0.9977* (0.0002)	0.0354* (0.0007)	2.5402
ICI	-1.3522* (0.0661)	0.0000 (0.0000)	0.1224 (0.9767)	3.0608* (1.0000)	0.2576
Ladbroke	-0.7733* (0.1990)	3.1387* (1.0000)	0.9950* (0.0008)	0.0529* (0.0010)	3.2740
Land Securities	-1.5183* (0.0711)	2.4573* (1.0000)	0.8523* (0.0656)	0.4192* (0.0411)	0.9961
Legal & General	-0.7165* (0.1474)	2.2582* (1.0000)	0.9829* (0.0050)	0.1290* (0.0062)	2.1954
Marks & Spencer	-1.0464* (0.1400)	2.5073* (1.0000)	0.9927* (0.0011)	0.0525* (0.0011)	1.8559
Natwest Bank	-0.6622* (0.0918)	2.3626* (1.0000)	0.9440* (0.0234)	0.2376* (0.0172)	2.2553
Pearson	-1.0653* (0.0836)	2.3720* (1.0000)	0.8965* (0.0515)	0.3855* (0.0416)	1.6112
Prudential	-0.6950* (0.1223)	2.2918* (1.0000)	0.9814* (0.0054)	0.1137* (0.0048)	2.2542
RMC	-1.2140* (0.1153)	2.6614* (1.0000)	0.9677* (0.0118)	0.1780* (0.0092)	1.8502
Rank Group	-1.1199* (0.1164)	2.9625* (1.0000)	0.9433* (0.0244)	0.3062* (0.0238)	1.9611
Reckitt & Colman	-1.4179* (0.0814)	2.2217* (1.0000)	0.9213* (0.0363)	0.2902* (0.0264)	1.0684

Table 6.1 (continued). Stochastic Volatility Conditional Mean and Variance Specifications

Stock/Index	Λ_t	σ_ξ	Φ	σ_η	k^2
Reed International	-1.0540* (0.0625)	2.2834* (1.0000)	0.7012* (0.1432)	0.7125* (0.1184)	1.3239
Reuters	-0.6284* (0.0527)	1.6317 (1.0000)	0.2726 (0.4899)	1.6404 (41.090)	0.8711
Rio Tinto	-1.0198* (0.0714)	2.3944* (1.0000)	0.7505* (0.1342)	0.7272* (0.1312)	1.3690
Royal & Sun Alliance Ins.	-0.6601 (0.5064)	2.5570* (1.0000)	0.9982* (0.0003)	0.0563* (0.0015)	2.8028
Royal Bank of Scotland	-0.7667* (0.0679)	2.3359* (1.0000)	0.7910* (0.1027)	0.5685* (0.0786)	2.0375
Sainsbury	-0.9730* (0.1848)	2.5010* (1.0000)	0.9960* (0.0005)	0.0401* (0.0008)	1.9088
Scottish & Newcastle	-1.1207* (0.0905)	2.2090* (1.0000)	0.9085* (0.0490)	0.3882* (0.0489)	1.4295
Standard Chartered	-0.5353* (0.1959)	2.4872* (1.0000)	0.9879* (0.0030)	0.1239* (0.0053)	3.1780
Unilever	-1.2873* (0.1673)	2.2151* (1.0000)	0.9906* (0.0019)	0.0824* (0.0029)	1.1592

Notes: Figures in parentheses are standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 6.2. Stochastic Volatility Model Residual Diagnostics

Stock/Index	Mean	S.D.	Skewness	Kurtosis	JB	Q_5	Q_{10}	Q_5^2	Q_{10}^2
FTSE 100	-0.0073	1.0000	-1.2862	5.6091	1,558*	2.9021	8.6942	1.8344	5.3776
Asda	-0.0077	1.0000	-1.1884	3.2426	661*	8.4518*	10.040	39.884*	72.595*
Associated British Foods	0.0105	0.9999	-0.5519	2.5151	168*	23.904*	32.215*	6.9338	11.273
BAA	0.0483	0.9988	-0.6331	2.6661	199*	6.9789	8.4045	9.4065*	14.936
BAT Industries	0.0300	0.9996	-0.9079	3.3352	395*	6.2530	8.7185	19.589*	22.904*
BOC	-0.0076	1.0000	-1.0311	3.5954	534*	10.822*	16.698*	18.616*	21.268*
BG	0.0453	0.9990	-0.8741	3.1323	356*	7.5422	15.933*	15.579*	19.092*
BT	0.0292	0.9996	-0.8623	3.2169	351*	5.8756	8.2691	39.362*	42.589*
Barclays	0.0066	1.0000	-1.0050	4.3683	685*	9.2822*	27.216*	2.9630	37.228*
Bass	0.0560	0.9984	-0.9975	3.6881	516*	7.8727*	10.312	25.478*	27.458*
Blue Circle	0.0261	0.9997	-1.5482	4.6849	1,439*	8.3106*	13.196	30.639*	34.408*
Boots	-0.0569	0.9984	-0.8843	3.3233	375*	10.960*	14.680	3.5731	5.8462
British Airways	-0.0140	0.9999	-0.9854	3.3708	467*	6.1316	9.2594	19.548*	22.373*
CGU	-0.0029	1.0000	-0.9651	3.4289	453*	26.203*	30.601*	31.200*	35.205*
Cadbury Schweppes	-0.0670	0.9978	-0.7593	2.9675	267*	1.6027	8.9035	4.1148	8.8919
Diageo	0.0091	1.0000	-0.7075	2.8964	233*	14.248*	22.674*	12.023*	14.813
EMI	0.0067	1.0000	-0.8747	3.3350	368*	21.115*	21.962*	21.981*	25.259*
Enterprise Oil	-0.0451	0.9990	-1.2400	4.0541	841*	4.4925	10.169	17.516*	20.982*
General Electric	0.0267	1.0000	-0.9118	3.1070	387*	1.9753	4.5727	22.950*	37.290*
Glaxo Wellcome	0.0067	1.0000	-1.2594	5.2583	1,326*	8.6315*	10.220	17.841*	22.308*
ICI	0.0361	0.9994	-1.6874	5.9436	2,327*	8.5797*	11.436	43.923*	46.842*
Ladbroke	0.0131	0.9999	-1.4773	4.5013	1,274*	7.6726	10.087	9.8727*	16.647*
Land Securities	-0.0620	0.9981	-1.0031	3.4600	492*	7.2822	16.685*	32.788*	35.489*
Legal & General	-0.0120	0.9999	-0.7709	3.1816	280*	19.380*	22.322*	8.7361*	12.258
Marks & Spencer	-0.0079	1.0000	-0.9378	3.1402	410*	7.6888	11.437	14.332*	17.753*
Natwest Bank	0.0453	0.9990	-0.9454	3.3738	430*	10.670*	18.088*	21.265*	22.993*
Pearson	0.0446	0.9990	-0.7964	2.9907	294*	15.099*	19.545*	13.521*	14.909
Prudential	0.0117	0.9999	-0.8490	3.2362	340*	10.544*	12.276	18.694*	19.549*
RMC	0.0080	1.0000	-0.9576	3.3938	443*	4.9754	12.870	23.587*	25.031*
Rank Group	0.0398	0.9992	-1.4914	4.9488	1,473*	14.311*	20.665*	14.024*	20.303*
Reckitt & Colman	0.0151	0.9999	-0.7081	3.0143	233*	11.155*	15.818*	13.803*	20.883*

Table 6.2 (continued). Stochastic Volatility Model Residual Diagnostics

Stock/Index	Mean	S.D.	Skewness	Kurtosis	JB	Q_5	Q_{10}	Q_5^2	Q_{10}^2
Reed International	-0.0283	0.9996	-0.9255	3.3929	415*	9.3884*	15.210	6.6161	10.336
Reuters	-0.0003	1.0000	-0.8483	3.3667	349*	8.7648*	13.609	7.0236	10.538
Rio Tinto	-0.0303	0.9995	-1.1570	4.0170	740*	9.6224*	15.958*	38.505*	48.974*
Royal & Sun Alliance Ins.	0.0225	0.9997	-1.1253	3.8080	662*	24.221*	38.927*	17.266*	22.531*
Royal Bank of Scotland	0.0595	0.9982	-0.7190	2.7987	244*	15.570*	18.970*	12.643*	18.728*
Sainsbury	-0.0045	1.0000	-1.0666	3.5245	559*	21.904*	25.266*	32.350*	48.842*
Scottish & Newcastle	-0.0387	0.9993	-0.7629	3.1075	271*	4.0578	8.9275	2.6405	3.4921
Standard Chartered	0.0153	0.9999	-0.8347	3.1708	326*	33.044*	38.364*	16.409*	18.506*
Unilever	-0.0193	0.9998	-0.8294	3.4142	339*	10.348*	15.296	3.6183	12.662

Notes: S.D. denotes the standard deviation. The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, $JB \sim \chi_2^2$. An asterisk denotes significance in the JB statistic at the 5% level. Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with (i - n + 1) degrees of freedom, where n is the number of hyperparameters. An asterisk denotes significance at the 5% level.

Table 6.3. Stochastic Volatility Conditional Mean and Variance Specifications (Monday Effect)

The following mean and variance specifications are used:

$$\ln(y_t^2) = \Lambda + \lambda_d M_t + h_t + \xi_t, \quad h_{t+1} = \Phi h_t + \eta_t$$

where $\Lambda = \ln(k^2) + E_t[\ln(\epsilon_t^2)]$, $\ln(k^2) = \left(\frac{\delta}{1 - \Phi}\right)$ and $M_t = 1$ when the day of the week is Monday and zero otherwise.

Stock/Index	Λ	σ_ξ	Φ	σ_η	k^2	λ_d
Asda	-1.0529* (0.1233)	3.7606* (1.0000)	0.9358* (0.0230)	0.3197* (0.0178)	3.8477	-0.5881* (0.1785)
BAA	-1.0983* (0.0776)	2.1256* (1.0000)	0.8634* (0.0762)	0.4553* (0.0656)	1.1449	-0.4134* (0.1020)
BAT Industries	-0.7471* (0.0911)	2.3316* (1.0000)	0.9698* (0.0094)	0.1228* (0.0053)	2.1610	-0.3127* (0.1105)
BOC	-1.1405* (0.2414)	2.5051* (1.0000)	0.9945* (0.0007)	0.0725* (0.0021)	1.5210	-0.4382* (0.1187)
BG	-0.8542* (0.0618)	2.2198* (1.0000)	0.5293* (0.2091)	0.9770* (0.2088)	1.2890	-0.5614* (0.1125)
Barclays	-0.6607* (0.0873)	2.2456* (1.0000)	0.9045* (0.0485)	0.3695* (0.0416)	1.8678	-0.4777* (0.1072)
Bass	-1.0872* (0.0619)	2.1902* (1.0000)	0.6273* (0.1693)	0.7967* (0.1459)	1.0790	-0.3204* (0.1084)
Blue Circle	-0.7870* (0.1072)	3.1864* (1.0000)	0.9348* (0.0243)	0.2874* (0.0171)	2.5846	-0.7671* (0.1513)
Boots	-0.9074* (0.0588)	2.2261* (1.0000)	0.7206* (0.1000)	0.5152* (0.0513)	1.4778	-0.2628* (0.1073)
British Airways	-0.6411* (0.0778)	2.3904* (1.0000)	0.8521* (0.0732)	0.4606* (0.0545)	2.1017	-0.3814* (0.1144)
CGU	-0.6332* (0.2457)	2.4087* (1.0000)	0.9967* (0.0006)	0.0454* (0.0010)	2.2512	-0.6315* (0.1141)
Cadbury Schweppes	-0.9659* (0.0584)	2.1390* (1.0000)	0.5364* (0.1942)	0.8842* (0.1675)	1.1787	-0.3894* (0.1076)
Diageo	-0.8926* (0.2087)	2.2870* (1.0000)	0.9939* (0.0009)	0.0685* (0.0020)	1.8957	-0.4232* (0.1084)
EMI	-1.2022* (0.0787)	2.3927* (1.0000)	0.8944* (0.0460)	0.3362* (0.0292)	1.3511	-0.3669* (0.1140)
Enterprise Oil	-1.0701* (0.0836)	2.7272* (1.0000)	0.7053* (0.1571)	0.9342* (0.1868)	1.4350	-0.6535* (0.1341)
General Electric	-0.9522* (0.0772)	2.4914* (1.0000)	0.9324* (0.0226)	0.2015* (0.0102)	1.7966	-0.2736* (0.1182)

Table 6.3 (continued). Stochastic Volatility Conditional Mean and Variance Specifications (Monday Effect)

Stock/Index	Λ	σ_ξ	Φ	σ_η	k^2	λ_d
Glaxo Wellcome	-0.4799 (0.2585)	2.3417* (1.0000)	0.9976* (0.0001)	0.0355* (0.0007)	2.5402	-0.4102* (0.1109)
ICI	-1.1961* (0.0714)	0.0000 (0.0000)	0.1233 (0.9758)	3.0441* (1.0000)	0.2687	-0.7803* (0.1390)
Ladbroke	-0.6981* (0.2011)	3.1356* (1.0000)	0.9950* (0.0008)	0.0530* (0.0010)	3.2734	-0.3762* (0.1486)
Land Securities	-1.4328* (0.0747)	2.4496* (1.0000)	0.8497* (0.0675)	0.4262* (0.0426)	0.9928	-0.4278* (0.1171)
Legal & General	-0.6526* (0.1480)	2.2543* (1.0000)	0.9826* (0.0051)	0.1303* (0.0063)	2.1925	-0.3225* (0.1069)
Marks & Spencer	-0.9599* (0.1408)	2.5014* (1.0000)	0.9925* (0.0014)	0.0535* (0.0012)	1.8541	-0.4353* (0.1185)
Natwest Bank	-0.5765* (0.0934)	2.3541* (1.0000)	0.9410* (0.0250)	0.2466* (0.0185)	2.2467	-0.4289* (0.1119)
Pearson	-0.9934* (0.0861)	2.3655* (1.0000)	0.8935* (0.0533)	0.3938* (0.0435)	1.6042	-0.3605* (0.1129)
Prudential	-0.6341* (0.1235)	2.2884* (1.0000)	0.9811* (0.0056)	0.1151* (0.0049)	2.2524	-0.3053* (0.1085)
RMC	-1.0498* (0.1068)	2.6264* (1.0000)	0.9523* (0.0188)	0.2309* (0.0148)	1.8115	-0.8342* (0.1247)
Rank Group	-0.9883* (0.1194)	2.9494* (1.0000)	0.9423* (0.0249)	0.3107* (0.0246)	1.9577	-0.6586* (0.1401)
Reckitt & Colman	-1.3363* (0.0839)	2.2146* (1.0000)	0.9199* (0.0372)	0.2946* (0.0272)	1.0658	-0.4084* (0.1054)
Reed International	-0.9594* (0.0662)	2.2692* (1.0000)	0.6940* (0.1485)	0.7306* (0.1263)	1.3095	-0.4732* (0.1111)
Reuters	-0.4859* (0.0577)	1.8780 (1.0000)	0.3979 (0.3338)	1.2844* (0.5990)	1.2189	-0.7113* (0.1043)
Rio Tinto	-0.9348* (0.0753)	2.3871* (1.0000)	0.7530* (0.1337)	0.7242* (0.1314)	1.3700	-0.4749* (0.1163)
Royal & Sun Alliance Insurance	-0.5264 (0.5023)	2.5423* (1.0000)	0.9982* (0.0001)	0.0568* (0.0015)	2.8031	-0.6660* (0.1205)
Sainsbury	-0.9248* (0.0732)	2.4283* (1.0000)	0.8823* (0.0467)	0.3241* (0.0246)	1.9088	-0.5674* (0.1156)
Standard Chartered	-0.4261* (0.1942)	2.4764* (1.0000)	0.9874* (0.0032)	0.1270* (0.0056)	3.1647	-0.5569* (0.1174)

Notes: Figures in parentheses are standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 6.4. Log Likelihood Values for the Volatility Models					
Stock/Index	**GARCH**	**GJR**	**CGARCH**	**ACGARCH**	**SV**
FTSE 100	-3,287.232	-3,280.195	–	–	-3,373.142
Asda	-5,813.340	–	-5,813.407	–	7,949.122
Associated British Foods	-4,073.127	-4,058.662	-4,070.646	–	4,053.194
BAA	-4,452.328	–	-4,451.970	–	-4,153.653
BAT Industries	-5133.532	–	–	–	5,560.497
BOC	-4,455.778	–	–	–	4,529.649
BG	-4,936.153	–	-4,929.083	–	4,411.966
BT	-4,584.309	–	-4,584.125	–	-4,558.530
Barclays	-5,053.585	–	-5,054.114	-5,047.220	5,166.392
Bass	-4508.380	–	-4507.278	–	4,016.808
Blue Circle	-5,342.656	-5,329.980	-5,339.583	–	6,173.587
Boots	-4751.349	–	-4749.118	-4739.114	-4,619.087
British Airways	-5,234.301	–	-5,233.699	-5,223.944	-5489.366
CGU	-4911.558	–	-4908.849	-4904.732	-5,516.887
Cadbury Schweppes	-4,761.393	–	-4,758.563	-4,750.325	4,035.209
Diageo	-4790.324	-4775.016	-4779.451	–	5,060.236
EMI	-4,566.559	-4,553.407	-4,565.153	–	4,443.983
Enterprise Oil	-5,090.134	–	-5,063.702	–	4,568.442
General Electric	-4849.525	–	-4847.406	-4841.941	-5,060.543
Glaxo Wellcome	-5193.716	–	-5188.384	–	6,025.476
ICI	-4,649.823	-4,638.508	-4,648.628	–	-2,918.855
Ladbroke	-5,549.819	-5,526.181	-5,549.076	–	6,299.715
Land Securities	-4,168.719	–	-4,162.461	–	-3,943.268
Legal & General	-5,096.101	–	-5,094.725	–	-5,560.612
Marks & Spencer	-4777.875	–	-4777.206	–	5,240.975
Natwest Bank	-5231.379	–	–	–	5,696.974
Pearson	-4,866.123	–	-4,867.110	–	4,796.087
Prudential	-5127.004	–	-5126.588	–	5,683.260
RMC	-4,879.934	-4,869.718	-4,877.910	–	5,122.785

Table 6.4 (continued). Log Likelihood Values for the Volatility Models

Stock/Index	GARCH	GJR	CGARCH	ACGARCH	SV
Rank Group	-5,062.019	-5,057.020	-5,061.593	–	-5,278.519
Reckitt & Colman	-4,235.045	–	-4,235.080	–	-4,035.490
Reed International	-4,760.557	-4,752.243	-4,760.465	–	4,400.712
Reuters	-5184.456	-5174.498	-5182.457	–	3,771.475
Rio Tinto	-4,762.766	-4,747.174	-4,758.668	–	4,463.898
Royal & Sun Alliance Ins.	-5,306.649	-5,271.068	–	–	6,323.473
Royal Bank of Scotland	-5,299.697	–	-5,297.014	–	5,394.734
Sainsbury	-4776.296	–	-4775.875	–	5,123.484
Scottish & Newcastle	-4,844.374	–	–	–	4,538.823
Standard chartered	-5,557.861	-5,558.517	-5,557.920	–	6,895.741
Unilever	-4083.373	–	-4,078.124	–	4,059.995

Notes: The log likelihood values refer to the equation specifications shown in tables 3.2, 3.5 and 6.1. The log likelihood values for the stochastic volatility model are adjusted to make them comparable with the ARCH type models. The log likelihood transformation as proposed by Hansson and Hördahl (1998) is given by:

$$Lnl(t) = [-\ln(2\pi) - (h_t) - (y_t^2/\exp(h_t))]/2$$

where y_t is the mean adjusted return and h_t is the log-variance obtained from the Kalman filter.

Table 6.5. Schwarz Criterion Values for the Volatility Models					
Index	**GARCH**	**GJR**	**CGARCH**	**ACGARCH**	**SV**
FTSE 100	2.375762	2.373556	–	–	2.433757
Asda	4.191839	–	4.19887	–	5.711399
Associated British Foods	2.943191	2.935648	2.944258	–	2.913605
BAA	3.218454	–	3.218197	–	2.997858
BAT Industries	3.704969	–	–	–	3.996049
BOC	3.215235	–	–	–	3.255763
BG	3.560332	–	3.560951	–	3.171251
BT	3.310420	–	3.313137	–	3.285023
Barclays	3.650392	–	3.650772	3.648669	3.713029
Bass	3.255872	–	3.257930	–	2.887475
Blue Circle	3.855209	3.851736	3.855850	–	4.436329
Boots	3.427570	–	3.431666	3.427328	3.328511
British Airways	3.780217	–	3.779785	3.775626	3.953487
CGU	3.545512	–	3.546415	3.546307	3.964731
Cadbury Schweppes	3.434786	–	3.438451	3.435156	2.900689
Diageo	3.455570	3.450271	3.453457	–	3.636795
EMI	3.297668	3.291069	3.299507	–	3.194243
Enterprise Oil	3.670951	–	3.657660	–	3.283621
General Electric	3.498099	–	3.502275	3.501198	3.637015
Glaxo Wellcome	3.745363	–	3.747230	–	4.329965
ICI	3.357484	3.352204	3.359475	–	2.107518
Ladbroke	4.006882	3.992750	4.006348	–	4.526905
Land Securities	3.009014	–	3.010217	–	2.843183
Legal & General	3.678086	–	3.679947	–	4.004651
Marks & Spencer	3.449476	–	3.451844	–	3.766589
Natwest Bank	3.777268	–	–	–	4.094057
Pearson	3.515721	–	3.516430	–	3.447101
Prudential	3.703135	–	3.702837	–	4.084209
RMC	3.522794	3.521153	3.524189	–	3.690232

Table 6.5 (continued). Schwarz Criterion Values for the Volatility Models

Index	GARCH	GJR	CGARCH	ACGARCH	SV
Rank Group	3.653602	3.652860	3.656145	–	3.802070
Reckitt & Colman	3.062361	–	3.062386	–	2.909410
Reed International	3.437035	3.433911	3.439817	–	3.171688
Reuters	3.741560	3.737255	3.742972	–	2.719812
Rio Tinto	3.438622	3.433119	3.438526	–	3.217064
Royal & Sun Alliance Ins.	3.826493	3.803781	–	–	4.552486
Royal Bank of Scotland	3.824348	–	3.825269	–	3.885528
Sainsbury	3.448341	–	3.450887	–	3.690734
Scottish & Newcastle	3.494399	–	–	–	3.270870
Standard chartered	4.012659	4.015980	4.012702	–	4.963450
Unilever	2.950552	–	2.949630	–	2.927008

Notes: The Schwarz criterion values refer to the equation specifications shown in tables 3.2, 3.5 and 6.1. The Schwarz criterion values for the stochastic volatility model are based on adjusted log likelihood values to make them comparable with the ARCH type models. The log likelihood transformation as proposed by Hansson and Hördahl (1998) is given by:

$$Lnl(t) = [-\ln(2\pi) - (h_t) - (y_t^2/\exp(h_t))]/2$$

where y_t is the mean adjusted return and h_t is the log-variance obtained from the Kalman filter.

Table 6.6. Forecast Error Statistics for the Stochastic Volatility Model

The one-step ahead forecast of the conditional variance is given by:

$$h_{t+1} = k^2 \exp(h_{t|T})^{\Phi}$$

where $\exp(h_{t|T})$ is the smoothed estimate of the volatility process.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
FTSE 100	RMSE	4.5266	5.8554	2.1935*	3.1061*	3.6096	1.2723
	MAE	3.3444*	3.7703	2.0133	2.0550	2.1981	1.0520
	MedAPE	0.8621	1.0131	2.1065	2.7684	0.7317*	2.0830
	MedSE	2.9529	4.4595	3.4792	2.3426	0.9846	1.1284
Asda	RMSE	7.3732	9.7387*	8.9606	11.167	5.8535	6.9691
	MAE	6.2012	7.8935	7.9868	10.375	4.9935	6.6883
	MedAPE	3.0822	0.9410	2.1982	8.5642	2.1442	4.2261
	MedSE	33.246	33.150	76.306	148.85	21.330	48.305
Associated British Foods	RMSE	8.9681*	16.876	11.237	27.852*	11.963*	9.5219
	MAE	7.5542*	11.462	9.5462	19.961	9.4667	8.7448
	MedAPE	0.7400*	1.3562	3.0487	0.8544	1.4731	3.0122
	MedSE	50.527	70.219	160.12	182.21	85.019	85.548
BAA	RMSE	5.9311	4.0751	5.3396	6.0376*	2.6465	7.6444
	MAE	3.5300	2.9713	3.7533	3.0155*	1.7237*	3.8284*
	MedAPE	0.9690*	0.7682	0.8439	3.3943	2.0059	0.9628*
	MedSE	2.3758	3.9479	5.1051	1.8294*	0.8803*	1.5371*
BAT Industries	RMSE	231.61*	12.720	8.9314*	9.4354	47.036	4.0935*
	MAE	57.778*	9.1471	5.4191	6.3327*	18.894*	3.1547*
	MedAPE	0.6752*	0.8536	1.8460	0.6479	0.9332	0.4421*
	MedSE	18.334	24.472	16.739	19.564	28.470	7.0498*
BOC	RMSE	4.5782	7.5654*	14.149*	3.4763	3.6258	8.8317
	MAE	3.7994	5.3571	8.0020	3.2469	2.9138	4.7275*
	MedAPE	0.6895	0.6084*	5.9700	4.8330	2.6773	0.7541*
	MedSE	17.210	28.241	38.276	11.166	5.1246	4.8519
BG	RMSE	10.950	6.7984	2.9529	5.0208	13.079	7.9031
	MAE	6.1193*	4.0856	1.8917*	2.6956*	6.1102	4.7071*
	MedAPE	0.9190	0.8136	1.5455	5.4295	1.1196	0.8586
	MedSE	2.0036*	2.8058*	1.3900	1.6155*	2.7509*	2.9561*

Table 6.6 (continued). Forecast Error Statistics for the Stochastic Volatility Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
BT	RMSE	7.6378	10.875	11.195	4.6577*	9.7109	24.484
	MAE	4.8937	7.4639*	7.6372*	3.9287	6.2008	9.2079
	MedAPE	0.8404	0.8713	0.8049	1.8656	0.8946	1.3820
	MedSE	9.5265	15.269	12.862	14.861	7.8790	13.688
Barclays	RMSE	26.434	23.758	17.339	6.7638*	12.185	13.889
	MAE	16.868*	15.661	10.452*	4.7369	7.3164	10.041
	MedAPE	0.8976*	0.6228	0.6841*	0.8776*	1.5040	0.8066
	MedSE	32.282*	100.76*	33.746	10.089	8.8898	48.948
Bass	RMSE	40.652	13.627	20.233	7.7887*	18.526	10.855*
	MAE	18.950	8.1063	10.991*	6.5164	8.2681*	6.7945
	MedAPE	0.9054	0.9965	0.8114*	2.1452	0.8254	1.3541
	MedSE	24.182	22.514	19.190	35.385	6.9983	17.890
Blue Circle	RMSE	21.895	9.8925*	6.1337	3.9543	7.7903*	12.724*
	MAE	13.979*	7.9973	5.3965	3.5981	5.3595*	8.2818
	MedAPE	0.8522*	0.7766*	2.6546	3.7872	1.6703	0.8433
	MedSE	47.084	41.455	25.568	12.837	10.310	22.383
Boots	RMSE	3.9806	4.0838	17.964*	4.9701*	11.372	6.9086
	MAE	2.8168	3.5114	7.3917	3.9161	6.1373*	4.5464*
	MedAPE	0.8316	0.6792*	1.9997	1.1683	0.8908*	0.9226*
	MedSE	3.5196*	11.745*	9.0068	8.0942	3.4185*	3.7005*
British Airways	RMSE	21.529	16.754	10.556	8.8712	9.6196	6.8736
	MAE	14.914*	11.880	6.3017	6.0014	6.1686*	5.7339
	MedAPE	0.9117	0.7076	1.0817	0.8775	0.7858	0.7684
	MedSE	27.021*	74.302	14.818	18.045	11.221	19.960
CGU	RMSE	30.274	34.157	17.367	11.495	8.8090	5.7973
	MAE	19.131	16.901	12.514	10.668	6.4704	4.9120
	MedAPE	0.8614	1.6086	1.6589	5.3444	0.7465	0.6364
	MedSE	57.563*	74.923	91.299	115.94	28.439	21.039

Table 6.6 (continued). Forecast Error Statistics for the Stochastic Volatility Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Cadbury Schweppes	RMSE	7.4054	16.142	3.5854	7.4770*	5.5732	6.7071*
	MAE	4.1870	9.6161*	3.1571	4.7779	3.7525	4.2947
	MedAPE	0.9392	0.8948	2.7830	2.5136	1.9363	1.9162
	MedSE	3.4999*	24.387	13.721	12.654	5.7089	7.5904
Diageo	RMSE	29.236	18.029	11.892	14.630*	8.4309	8.2959
	MAE	17.319*	14.297	8.9906	12.073	5.3440	6.1105
	MedAPE	0.8696	3.1442	2.0173	1.4900	3.5488	1.9420
	MedSE	47.548	150.30	57.508	111.16	11.533	20.045
EMI	RMSE	65.275	11.060*	53.905	5.9070	8.0013	18.185
	MAE	27.628*	7.1147	19.387	4.6802	4.7117	9.2277
	MedAPE	0.8527*	1.0346	1.2019	6.2543	0.9139	1.4512
	MedSE	50.742*	22.602	26.930	15.597	5.7759	4.6008
Enterprise Oil	RMSE	30.037	7.1261	11.044	5.4737*	10.990	6.2349*
	MAE	17.994*	4.8203	8.0026*	3.4911	5.0773*	4.2385*
	MedAPE	0.8689*	0.7439	0.8089	3.2012	0.9260	0.7553*
	MedSE	15.557	8.4176	17.281	5.2311	5.4912	7.9885
General Electric	RMSE	18.780	12.350	8.5557	31.738	10.331	6.7044*
	MAE	10.073*	7.1482	5.5617	14.574	6.5712	4.2311
	MedAPE	0.8088	1.8405	0.8743	0.9570*	0.7965	1.0921
	MedSE	21.090*	9.2304	10.605	13.493	8.0814	8.0144
Glaxo Wellcome	RMSE	7.8142	13.639	3.1781	3.4445	5.9146	5.7186
	MAE	5.1533	7.3550	2.7412	2.8406	4.0143	3.6932
	MedAPE	0.8647*	4.3167	6.5422	1.8531	1.0056	0.6842
	MedSE	13.447	17.257	8.4189	6.9614	7.7393*	7.0075*
ICI	RMSE	19.716	42.488	9.8961	8.7585	19.226	18.459
	MAE	11.133	24.715	6.7050	4.6150*	11.061	8.1045
	MedAPE	0.9621	0.9770	0.9565	0.9186*	0.9660	0.9480
	MedSE	14.675	38.427	10.843	0.3156*	5.6664	5.5853

Table 6.6 (continued). Forecast Error Statistics for the Stochastic Volatility Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Ladbroke	RMSE	29.829	13.060	23.061	10.243	14.322	50.732*
	MAE	18.206	9.6958	14.965	9.4210	9.2903	17.706
	MedAPE	0.7779	0.7826*	1.7215	3.0355	2.9929	1.3375
	MedSE	62.618*	70.006	92.131	102.50	32.575	32.666
Land Securities	RMSE	3.8661	3.4563	2.6318	1.8283*	4.4659	5.1155
	MAE	2.2748	2.5482	1.5698	1.4166	2.5947	2.6555
	MedAPE	0.9055	1.4637	0.6565	1.1317	0.9026	2.4171
	MedSE	1.3152*	2.7651	0.7381*	1.1781	0.9906*	1.6112
Legal & General	RMSE	35.272	32.021	9.9742	9.5555	17.530	9.9726
	MAE	19.163	16.456	8.8300	7.4798	7.4288	6.5649
	MedAPE	2.0289	0.8381	1.1147	1.2923	1.0870	0.9360
	MedSE	33.357	61.732	85.443	43.225	16.193	14.300
Marks & Spencer	RMSE	11.639	7.2126	25.545	9.7751	47.647	4.0879
	MAE	6.9750*	4.4445	10.283	6.0467	13.777	3.7362
	MedAPE	0.8485	0.9328	0.9344	2.0846	0.5822	11.699
	MedSE	9.1093	9.3720	11.725	13.448	12.031	14.998
Natwest Bank	RMSE	15.213	21.670*	10.827*	8.3824	21.600	13.617
	MAE	9.4772	13.464	7.7665	6.8259	10.818*	8.6289*
	MedAPE	0.7529*	1.0040	1.1476	1.2401	0.8149*	0.7127*
	MedSE	30.603	45.259	44.542	45.492	23.063	30.389
Pearson	RMSE	19.866	6.4243*	4.8529	6.3763	7.0213	8.1170
	MAE	11.950	4.5310*	4.0838	5.3420	3.9864	5.4202
	MedAPE	0.8647	0.5619*	0.7515	2.3144	0.8765*	1.7585
	MedSE	23.888	17.271	14.808	28.762	5.6174	9.2831
Prudential	RMSE	32.963	28.527	8.0877	5.5981	9.1877	8.8161
	MAE	12.984*	14.527	6.1238	4.6300	4.9049	5.9785
	MedAPE	0.8593*	0.9089	1.9851	2.4121	0.9087	0.7260
	MedSE	13.322	53.403	26.752	11.590	4.1350*	13.324

Table 6.6 (continued). Forecast Error Statistics for the Stochastic Volatility Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
RMC	RMSE	36.016	14.722	4.7445	6.8097	16.865	14.491
	MAE	19.622	9.4079	3.9959	3.6450	9.2753	7.7741
	MedAPE	1.0004*	1.7159	5.5531	5.2792	0.9565	1.6546
	MedSE	41.224*	29.209	12.729	6.0814	14.786	14.193
Rank Group	RMSE	22.565	16.596	19.118*	9.6932	15.168	25.270
	MAE	13.491*	11.172	9.6612	7.7991	7.1629	11.128
	MedAPE	0.7897*	0.9928	0.9727	1.9118	0.7732*	0.9058
	MedSE	38.968	27.338	30.695	52.442	10.095	18.318
Reckitt & Colman	RMSE	14.096	6.1032	52.895	2.4905	6.5478	17.239
	MAE	6.3392	3.7376*	13.906	1.7745	4.0766*	7.3894
	MedAPE	1.3101	0.7780	3.0818	2.9681	0.8683	0.9878
	MedSE	3.4681	3.1392	3.6054	1.4987	3.4157*	4.7098
Reed International	RMSE	11.516	8.2447	6.3511	14.114	10.236	16.199
	MAE	6.1790	5.2684	4.5071	8.2171	4.5868*	8.2345
	MedAPE	0.6808*	0.6955*	0.8044	2.0963	1.6442	0.9591
	MedSE	3.0412	6.6374	6.1161	24.577	1.6262*	4.6991*
Reuters	RMSE	42.032	27.832	5.7419	13.664	29.933	9.5528
	MAE	21.083	17.588*	5.0266	8.6528	13.160	7.0930
	MedAPE	0.8908*	0.8702*	2.9007	0.7484*	0.9841	0.6279
	MedSE	14.420	66.304	25.213	37.561	7.5479*	15.382
Rio Tinto	RMSE	10.607	6.1011	3.6430	4.6255*	4.5871	7.5472
	MAE	7.5784	4.0726*	2.7615	3.5330	2.8758*	4.6005
	MedAPE	1.0248	0.8205*	0.9116	2.2465	0.8070*	1.5291
	MedSE	10.327	6.2144	6.1085	6.8765	2.8828	6.6538
Royal & Sun Alliance Ins.	RMSE	39.956*	23.269	21.924	15.306	14.708	10.858
	MAE	22.063	17.983	15.768	14.383	8.1616*	8.9745
	MedAPE	0.8845	1.8751	2.8893	12.635	0.5758*	8.9457
	MedSE	96.146	181.17	224.85	233.07	19.899	59.785

Table 6.6 (continued). Forecast Error Statistics for the Stochastic Volatility Model

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Royal Bank of Scotland	RMSE	19.532	15.347	16.357	12.668	16.346	8.4680
	MAE	11.943	9.9296	12.384	9.1561	9.0374	6.2445
	MedAPE	0.8178*	0.7859*	0.7027	2.7841	1.7077	0.7323
	MedSE	28.775	45.729	66.251*	63.737	12.210	25.099
Sainsbury	RMSE	10.517	10.139	4.3727	6.5710	10.581	17.111
	MAE	4.7042	4.6079	3.0237*	4.7153	4.7337	5.6413*
	MedAPE	1.4747	0.9305	0.7853	1.5214	4.8658	1.2517
	MedSE	3.6135	3.2236	4.7035	14.318	6.5937	2.3110
Scottish & Newcastle	RMSE	9.4805*	17.248*	7.0745	10.220	11.444	4.7838
	MAE	5.1197	7.6257	3.7157	6.4357*	7.8809	3.6242
	MedAPE	0.7462	1.3474	0.8854*	0.7623*	0.9412	1.4650
	MedSE	13.150	9.4206	2.3762*	11.354	20.066	8.6370
Standard Chartered	RMSE	21.940*	30.082	16.745	12.847	46.141	9.8813
	MAE	15.713*	23.520	14.099	11.635	24.023	8.3699
	MedAPE	0.8243*	1.9041	1.8765	3.8492	1.4983	2.8226
	MedSE	165.88	367.86	214.30	175.35	44.129	76.922
Unilever	RMSE	19.717	18.856	8.3732	5.9126	11.219	13.676
	MAE	11.102	10.985	5.7085	5.0886	7.4115	8.0153
	MedAPE	0.8233	2.5003	2.7122	2.0507	0.9026	1.3858
	MedSE	13.293	46.695	27.193	23.225	14.325	12.737

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 6.7. Best Forecast Model for the GARCH type and Stochastic Volatility Models							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
FTSE 100	RMSE	GJR	GJR	SV	SV	GJR	SV
	MAE	SV	SV	GJR	GJR	GJR	SV
	MedAPE	GJR	SV	GJR	GJR	SV	SV
	MedSE	SV	SV	GJR	GJR	GJR	SV
Asda	RMSE	GJR	SV	ACGARCH	GJR	ACGARCH	ACGARCH
	MAE	ACGARCH	GJR	ACGARCH	GJR	ACGARCH	ACGARCH
	MedAPE	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH
	MedSE	ACGARCH	SV	ACGARCH	GJR	ACGARCH	ACGARCH
Associated British Foods	RMSE	SV	ACGARCH	ACGARCH	SV	SV	ACGARCH
	MAE	SV	GJR	GJR	SV	SV	ACGARCH
	MedAPE	SV	GJR	GJR	SV	SV	ACGARCH
	MedSE	ACGARCH	GJR	GJR	GJR	SV	ACGARCH
BAA	RMSE	ACGARCH	GJR	GJR	SV	SV	GJR
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	GJR	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
BAT Industries	RMSE	SV	SV	SV	SV	GJR	SV
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
BOC	RMSE	GJR	SV	SV	GJR	GJR	GJR
	MAE	GJR	GJR	GJR	GJR	SV	SV
	MedAPE	SV	SV	GJR	SV	SV	SV
	MedSE	GJR	GJR	GJR	GJR	SV	SV
BG	RMSE	ACGARCH	ACGARCH	SV	GJR	GJR	ACGARCH
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV

Table 6.7 (continued). Best Forecast Model for the GARCH type and Stochastic Volatility Models							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
BT	RMSE	SV	ACGARCH	GJR	SV	ACGARCH	SV
	MAE	SV	SV	SV	SV	ACGARCH	SV
	MedAPE	SV	GJR	SV	SV	ACGARCH	SV
	MedSE	SV	SV	SV	SV	SV	SV
Barclays	RMSE	GJR	ACGARCH	GJR	SV	GJR	GJR
	MAE	SV	ACGARCH	SV	SV	SV	ACGARCH
	MedAPE	SV	ACGARCH	SV	SV	SV	GJR
	MedSE	SV	SV	SV	SV	SV	GJR
Bass	RMSE	GJR	ACGARCH	ACGARCH	SV	ACGARCH	SV
	MAE	GJR	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Blue Circle	RMSE	GJR	SV	SV	SV	SV	SV
	MAE	SV	SV	SV	SV	SV	GJR
	MedAPE	SV	SV	SV	SV	SV	GJR
	MedSE	SV	SV	SV	SV	SV	GJR
Boots	RMSE	GJR	SV	SV	SV	ACGARCH	GJR
	MAE	ACGARCH	GJR	SV	SV	SV	SV
	MedAPE	ACGARCH	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
British Airways	RMSE	GJR	GJR	SV	ACGARCH	GJR	GJR
	MAE	SV	ACGARCH	SV	SV	SV	SV
	MedAPE	GJR	GJR	SV	SV	SV	ACGARCH
	MedSE	SV	ACGARCH	SV	SV	SV	SV
CGU	RMSE	GJR	ACGARCH	SV	GJR	ACGARCH	GJR
	MAE	ACGARCH	SV	SV	GJR	GJR	GJR
	MedAPE	GJR	SV	ACGARCH	GJR	ACGARCH	GJR
	MedSE	SV	SV	ACGARCH	GJR	SV	GJR

Table 6.7 (continued). Best Forecast Model for the GARCH type and Stochastic Volatility Models

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Cadbury Schweppes	RMSE	GJR	GJR	GJR	SV	ACGARCH	SV
	MAE	GJR	SV	GJR	SV	SV	ACGARCH
	MedAPE	ACGARCH	GJR	GJR	SV	SV	ACGARCH
	MedSE	SV	SV	GJR	GJR	ACGARCH	ACGARCH
Diageo	RMSE	GJR	GJR	GJR	SV	SV	ACGARCH
	MAE	SV	ACGARCH	GJR	GJR	SV	SV
	MedAPE	SV	ACGARCH	ACGARCH	GJR	SV	SV
	MedSE	SV	ACGARCH	GJR	ACGARCH	SV	SV
EMI	RMSE	ACGARCH	SV	GJR	SV	ACGARCH	ACGARCH
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Enterprise Oil	RMSE	ACGARCH	ACGARCH	GJR	SV	GJR	SV
	MAE	SV	SV	SV	ACGARCH	SV	SV
	MedAPE	SV	SV	GJR	ACGARCH	GJR	SV
	MedSE	SV	SV	SV	ACGARCH	ACGARCH	SV
General Electric	RMSE	GJR	GJR	GJR	GJR	ACGARCH	SV
	MAE	SV	SV	SV	SV	ACGARCH	SV
	MedAPE	ACGARCH	SV	SV	SV	ACGARCH	SV
	MedSE	SV	SV	SV	SV	SV	SV
Glaxo Wellcome	RMSE	ACGARCH	ACGARCH	GJR	SV	ACGARCH	ACGARCH
	MAE	SV	SV	GJR	GJR	SV	SV
	MedAPE	SV	SV	GJR	GJR	SV	SV
	MedSE	GJR	SV	GJR	GJR	SV	SV
ICI	RMSE	GJR	GJR	ACGARCH	GJR	ACGARCH	ACGARCH
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	ACGARCH	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV

Table 6.7 (continued). Best Forecast Model for the GARCH type and Stochastic Volatility Models

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Ladbroke	RMSE	ACGARCH	GJR	GJR	GJR	SV	SV
	MAE	ACGARCH	SV	GJR	GJR	SV	SV
	MedAPE	SV	SV	ACGARCH	GJR	SV	GJR
	MedSE	SV	SV	GJR	GJR	SV	SV
Land Securities	RMSE	GJR	GJR	GJR	SV	ACGARCH	GJR
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Legal & General	RMSE	GJR	GJR	ACGARCH	ACGARCH	GJR	ACGARCH
	MAE	SV	SV	ACGARCH	ACGARCH	SV	SV
	MedAPE	SV	SV	SV	ACGARCH	SV	SV
	MedSE	SV	SV	SV	ACGARCH	SV	SV
Marks & Spencer	RMSE	SV	ACGARCH	SV	GJR	SV	SV
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	GJR	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Natwest Bank	RMSE	GJR	SV	SV	GJR	GJR	GJR
	MAE	GJR	SV	SV	GJR	SV	SV
	MedAPE	SV	SV	GJR	GJR	SV	SV
	MedSE	SV	SV	SV	GJR	SV	SV
Pearson	RMSE	ACGARCH	SV	ACGARCH	ACGARCH	ACGARCH	GJR
	MAE	ACGARCH	SV	GJR	GJR	SV	SV
	MedAPE	ACGARCH	SV	GJR	GJR	SV	SV
	MedSE	SV	SV	ACGARCH	GJR	SV	SV
Prudential	RMSE	ACGARCH	GJR	GJR	GJR	ACGARCH	GJR
	MAE	SV	ACGARCH	GJR	GJR	SV	GJR
	MedAPE	SV	ACGARCH	GJR	SV	SV	GJR
	MedSE	SV	SV	GJR	SV	SV	SV

Table 6.7 (continued). Best Forecast Model for the GARCH type and Stochastic Volatility Models

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
RMC	RMSE	ACGARCH	GJR	SV	SV	ACGARCH	ACGARCH
	MAE	GJR	SV	SV	SV	ACGARCH	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Rank Group	RMSE	GJR	GJR	SV	ACGARCH	GJR	GJR
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	GJR	SV	SV	SV
	MedSE	SV	SV	GJR	SV	SV	SV
Reckitt & Colman	RMSE	GJR	GJR	SV	SV	GJR	GJR
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	GJR	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Reed International	RMSE	ACGARCH	GJR	GJR	ACGARCH	GJR	ACGARCH
	MAE	SV	SV	SV	GJR	SV	SV
	MedAPE	SV	SV	ACGARCH	SV	SV	SV
	MedSE	SV	SV	SV	GJR	SV	SV
Reuters	RMSE	GJR	SV	SV	ACGARCH	ACGARCH	ACGARCH
	MAE	SV	SV	SV	GJR	SV	GJR
	MedAPE	SV	SV	SV	SV	SV	ACGARCH
	MedSE	SV	SV	SV	GJR	SV	SV
Rio Tinto	RMSE	ACGARCH	GJR	SV	SV	GJR	ACGARCH
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	ACGARCH	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Royal & Sun Alliance Ins.	RMSE	SV	GJR	ACGARCH	ACGARCH	GJR	ACGARCH
	MAE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	SV	ACGARCH
	MedAPE	GJR	ACGARCH	ACGARCH	ACGARCH	SV	SV
	MedSE	SV	ACGARCH	ACGARCH	ACGARCH	SV	SV

Table 6.7 (continued). Best Forecast Model for the GARCH type and Stochastic Volatility Models

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Royal Bank of Scotland	RMSE	GJR	ACGARCH	GJR	ACGARCH	GJR	GJR
	MAE	SV	ACGARCH	GJR	SV	SV	GJR
	MedAPE	SV	SV	GJR	SV	SV	SV
	MedSE	SV	ACGARCH	SV	ACGARCH	SV	SV
Sainsbury	RMSE	ACGARCH	GJR	GJR	GJR	GJR	ACGARCH
	MAE	SV	SV	SV	GJR	SV	SV
	MedAPE	SV	ACGARCH	ACGARCH	ACGARCH	GJR	SV
	MedSE	SV	SV	SV	ACGARCH	SV	SV
Scottish & Newcastle	RMSE	SV	SV	SV	GJR	GJR	GJR
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Standard Chartered	RMSE	SV	ACGARCH	ACGARCH	GJR	GJR	SV
	MAE	SV	ACGARCH	ACGARCH	GJR	SV	SV
	MedAPE	SV	ACGARCH	GJR	GJR	SV	SV
	MedSE	SV	ACGARCH	ACGARCH	GJR	SV	SV
Unilever	RMSE	ACGARCH	GJR	ACGARCH	GJR	ACGARCH	GJR
	MAE	ACGARCH	ACGARCH	ACGARCH	GJR	GJR	SV
	MedAPE	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH	SV
	MedSE	SV	ACGARCH	ACGARCH	ACGARCH	SV	SV

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. GJR, ACGARCH and SV denote the GARCH/GJR, CGARCH/ACGARCH and stochastic volatility models respectively.

Table 6.8. Best Forecast Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
FTSE 100	RMSE	ES	GJR	SV	SV	ES	HM
	MAE	SV	HM	HM	HM	GJR	HM
	MedAPE	GJR	HM	HM	HM	HM	RW
	MedSE	HM	HM	HM	HM	HM	HM
Asda	RMSE	HM	SV	HM	HM	HM	ES
	MAE	HM	HM	HM	HM	ACGARCH	ACGARCH
	MedAPE	RW	HM	ACGARCH	RW	RW	RW
	MedSE	RW	HM	RW	GJR	RW	RW
Associated British Foods	RMSE	SV	ES	ACGARCH	SV	SV	HM
	MAE	SV	GJR	GJR	HM	HM	HM
	MedAPE	SV	HM	HM	ES	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
BAA	RMSE	ES	ES	ES	SV	HM	ES
	MAE	HM	HM	HM	SV	SV	SV
	MedAPE	SV	ES	GJR	RW	RW	SV
	MedSE	HM	HM	HM	SV	SV	SV
BAT Industries	RMSE	SV	ES	SV	ES	ES	SV
	MAE	SV	HM	HM	SV	SV	SV
	MedAPE	SV	RW	HM	ES	HM	SV
	MedSE	HM	HM	HM	HM	HM	SV
BOC	RMSE	ES	SV	SV	HM	GJR	ES
	MAE	HM	GJR	HM	HM	HM	SV
	MedAPE	ES	SV	HM	RW	RW	SV
	MedSE	HM	HM	HM	RW	HM	HM
BG	RMSE	ACGARCH	ACGARCH	HM	HM	ES	ACGARCH
	MAE	SV	HM	SV	SV	HM	SV
	MedAPE	RW	HM	RW	RW	RW	HM
	MedSE	SV	SV	RW	SV	SV	SV

Table 6.8 (continued). Best Forecast Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
BT	RMSE	ES	ACGARCH	ES	SV	ACGARCH	ES
	MAE	HM	SV	SV	HM	ACGARCH	HM
	MedAPE	HM	GJR	ES	HM	ACGARCH	HM
	MedSE	HM	HM	HM	HM	HM	HM
Barclays	RMSE	ES	ACGARCH	ES	SV	ES	ES
	MAE	SV	ACGARCH	SV	HM	HM	HM
	MedAPE	SV	ACGARCH	SV	SV	RW	GJR
	MedSE	SV	SV	HM	HM	HM	HM
Bass	RMSE	GJR	ACGARCH	ES	SV	ES	SV
	MAE	GJR	HM	SV	HM	SV	HM
	MedAPE	HM	HM	SV	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Blue Circle	RMSE	ES	SV	HM	HM	SV	SV
	MAE	SV	HM	HM	HM	SV	GJR
	MedAPE	SV	SV	HM	RW	RW	ES
	MedSE	HM	HM	HM	HM	ES	HM
Boots	RMSE	GJR	ES	SV	SV	ES	ES
	MAE	HM	HM	HM	HM	SV	SV
	MedAPE	HM	SV	RW	RW	SV	SV
	MedSE	SV	SV	RW	HM	SV	SV
British Airways	RMSE	GJR	ES	SV	ACGARCH	GJR	GJR
	MAE	SV	ACGARCH	HM	HM	HM	HM
	MedAPE	GJR	GJR	HM	HM	SV	ACGARCH
	MedSE	SV	ACGARCH	HM	HM	HM	HM
CGU	RMSE	ES	ACGARCH	ES	GJR	ES	GJR
	MAE	ES	HM	HM	HM	GJR	HM
	MedAPE	GJR	HM	HM	HM	ACGARCH	GJR
	MedSE	SV	HM	HM	HM	HM	HM

Table 6.8 (continued). Best Forecast Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Cadbury Schweppes	RMSE	ES	ES	SV	SV	ACGARCH	SV
	MAE	HM	SV	HM	HM	HM	HM
	MedAPE	ACGARCH	GJR	HM	HM	RW	RW
	MedSE	SV	HM	RW	HM	HM	HM
Diageo	RMSE	GJR	GJR	SV	SV	HM	ACGARCH
	MAE	SV	HM	HM	HM	HM	HM
	MedAPE	HM	HM	HM	HM	RW	RW
	MedSE	HM	HM	HM	HM	HM	HM
EMI	RMSE	ACGARCH	SV	GJR	HM	HM	ES
	MAE	SV	HM	HM	HM	HM	HM
	MedAPE	SV	RW	HM	RW	HM	HM
	MedSE	SV	HM	HM	RW	HM	HM
Enterprise Oil	RMSE	ACGARCH	HM	ES	SV	GJR	SV
	MAE	SV	HM	SV	ACGARCH	SV	SV
	MedAPE	SV	HM	GJR	RW	HM	SV
	MedSE	HM	HM	HM	RW	ACGARCH	HM
General Electric	RMSE	GJR	GJR	ES	ES	ACGARCH	SV
	MAE	SV	HM	HM	HM	ACGARCH	HM
	MedAPE	ACGARCH	HM	HM	SV	HM	HM
	MedSE	SV	HM	HM	HM	HM	HM
Glaxo Wellcome	RMSE	ES	ACGARCH	RW	HM	ES	ES
	MAE	HM	HM	RW	HM	HM	HM
	MedAPE	SV	RW	RW	RW	HM	ES
	MedSE	HM	HM	RW	RW	SV	SV
ICI	RMSE	ES	GJR	ACGARCH	GJR	ES	ACGARCH
	MAE	HM	HM	HM	SV	HM	HM
	MedAPE	ACGARCH	HM	HM	SV	HM	RW
	MedSE	HM	HM	HM	SV	HM	HM

Table 6.8 (continued). Best Forecast Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Ladbroke	RMSE	ACGARCH	GJR	GJR	GJR	ES	SV
	MAE	ES	HM	HM	HM	HM	HM
	MedAPE	ES	SV	HM	HM	RW	HM
	MedSE	SV	HM	HM	HM	HM	HM
Land Securities	RMSE	ES	ES	ES	SV	RW	ES
	MAE	HM	HM	HM	HM	RW	HM
	MedAPE	HM	RW	HM	RW	HM	RW
	MedSE	SV	HM	SV	RW	SV	HM
Legal & General	RMSE	GJR	ES	ACGARCH	ACGARCH	ES	ACGARCH
	MAE	HM	HM	HM	HM	HM	HM
	MedAPE	HM	RW	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Marks & Spencer	RMSE	ES	ES	ES	GJR	ES	HM
	MAE	SV	HM	HM	HM	SV	HM
	MedAPE	GJR	HM	HM	HM	SV	RW
	MedSE	HM	HM	HM	HM	HM	RW
Natwest Bank	RMSE	ES	SV	GJR	GJR	ES	ES
	MAE	GJR	HM	HM	HM	SV	SV
	MedAPE	SV	HM	HM	HM	SV	SV
	MedSE	HM	HM	HM	HM	HM	HM
Pearson	RMSE	ES	SV	SV	ACGARCH	ACGARCH	ES
	MAE	ACGARCH	SV	HM	HM	HM	HM
	MedAPE	ES	SV	GJR	HM	SV	RW
	MedSE	HM	HM	HM	HM	HM	HM
Prudential	RMSE	ACGARCH	GJR	GJR	HM	ACGARCH	ES
	MAE	SV	ACGARCH	HM	HM	HM	GJR
	MedAPE	SV	ACGARCH	HM	RW	HM	GJR
	MedSE	HM	HM	HM	RW	SV	HM

Table 6.8 (continued). Best Forecast Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
RMC	RMSE	ACGARCH	GJR	HM	HM	ACGARCH	ACGARCH
	MAE	GJR	HM	HM	HM	ACGARCH	HM
	MedAPE	SV	HM	RW	RW	ES	HM
	MedSE	SV	HM	HM	RW	HM	HM
Rank Group	RMSE	ES	ES	SV	ACGARCH	ES	ES
	MAE	SV	HM	HM	HM	HM	HM
	MedAPE	SV	HM	HM	HM	SV	HM
	MedSE	HM	HM	HM	HM	HM	HM
Reckitt & Colman	RMSE	GJR	ES	ES	HM	ES	ES
	MAE	HM	SV	HM	HM	SV	HM
	MedAPE	HM	GJR	RW	RW	SV	HM
	MedSE	HM	HM	HM	RW	HM	HM
Reed International	RMSE	ES	ES	GJR	ES	HM	ACGARCH
	MAE	HM	HM	HM	HM	SV	HM
	MedAPE	SV	SV	HM	HM	RW	RW
	MedSE	HM	HM	HM	HM	SV	SV
Reuters	RMSE	ES	ES	HM	ACGARCH	ES	ACGARCH
	MAE	HM	HM	HM	HM	HM	GJR
	MedAPE	SV	ACGARCH	HM	SV	HM	ACGARCH
	MedSE	HM	HM	HM	HM	SV	HM
Rio Tinto	RMSE	ES	GJR	HM	SV	GJR	ES
	MAE	HM	SV	HM	HM	SV	HM
	MedAPE	HM	SV	HM	RW	SV	HM
	MedSE	HM	HM	HM	HM	HM	HM
Royal & Sun Alliance Ins.	RMSE	SV	GJR	ES	HM	GJR	HM
	MAE	ACGARCH	HM	HM	HM	SV	HM
	MedAPE	HM	HM	HM	RW	SV	RW
	MedSE	ES	HM	HM	RW	HM	RW

Table 6.8 (continued). Best Forecast Model							
Stock/Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Royal Bank of Scotland	RMSE	GJR	ACGARCH	ES	ACGARCH	GJR	GJR
	MAE	HM	HM	GJR	HM	HM	GJR
	MedAPE	SV	SV	ES	HM	RW	HM
	MedSE	HM	HM	SV	HM	HM	HM
Sainsbury	RMSE	ES	ES	ES	ES	ES	ES
	MAE	HM	HM	SV	HM	HM	SV
	MedAPE	RW	HM	ACGARCH	HM	RW	HM
	MedSE	HM	HM	HM	HM	HM	RW
Scottish & Newcastle	RMSE	SV	SV	HM	ES	GJR	HM
	MAE	ES	HM	HM	SV	ES	HM
	MedAPE	ES	HM	SV	SV	ES	HM
	MedSE	HM	HM	SV	HM	HM	HM
Standard Chartered	RMSE	SV	ACGARCH	ACGARCH	HM	ES	HM
	MAE	SV	HM	HM	HM	HM	HM
	MedAPE	SV	HM	HM	HM	HM	HM
	MedSE	HM	HM	HM	HM	HM	HM
Unilever	RMSE	ACGARCH	GJR	ACGARCH	GJR	ES	ES
	MAE	ACGARCH	HM	HM	HM	GJR	HM
	MedAPE	HM	HM	HM	RW	ES	HM
	MedSE	HM	HM	HM	HM	HM	HM

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. GJR, ACGARCH, SV, HM, RW and ES denote the GARCH/GJR, CGARCH/ACGARCH, stochastic volatility, historical mean, random walk and exponential smoothing models respectively.

Table 6.9. Forecast Error Statistics for the Stochastic Volatility Model (Monthly Data)

The one-step ahead forecast of the conditional variance is given by:

$$h_{t+1} = k^2 \exp(h_{t|T})^{\Phi}$$

where $\exp(h_{t|T})$ is the smoothed estimate of the volatility process.

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	36.952*	31.452*	0.6184	1,157.2
Asda	41.604*	31.203*	0.2860	615.64*
Associated British Foods	208.35*	185.70*	0.8135*	24,123*
BAA	44.350	41.485	0.6501	2,361.0
BAT Industries	520.52	342.82	0.9391	32,354
BOC	44.383	39.879	0.3592	1,138.4
BG	80.451	72.426	0.8261	5,532.3
BT	130.89	126.82	0.8844	17,935
Barclays	206.74*	174.92*	0.6558*	24,612*
Bass	218.54	190.40	0.9544	28,761
Blue Circle	124.30	97.507	0.6826	8,553.4
Boots	87.214	78.272	0.8934	5,111.7
British Airways	184.18	137.84	0.5305	5,534.8
CGU	255.23	223.73	0.9323	40,062
Cadbury Schweppes	70.140*	47.871*	0.4786*	1,277.5
Diageo	202.85	170.17	0.8173	23,806
EMI	289.31	206.01	0.8263	10,463
Enterprise Oil	181.42	125.50	0.4973	8,099.5
General Electric	159.62	143.21	0.7879	14,041
Glaxo Wellcome	59.018	47.761	0.5570	2,459.5
ICI	192.99	136.61	0.4852	12,920
Ladbroke	238.17	214.46	0.7507	40,255
Land Securities	22.197	19.788	0.4205	352.44
Legal & General	230.18	203.14	0.9178	22,741
Marks & Spencer	149.18	128.55	0.8337	11,751

Table 6.9 (continued). Forecast Error Statistics for the Stochastic Volatility Model (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
Natwest Bank	143.06	110.93	0.4586*	10,321*
Pearson	116.96	97.051	0.7046	4,620.3
Prudential	158.41	120.99	0.5872	7,808.7
RMC	203.25	167.84	1.1458	16,607
Rank Group	146.91	110.10	0.4806	8,913.5
Reckitt & Colman	127.96	100.42	0.9134	6,998.3
Reed International	95.708	92.224	0.6795	7,155.2
Reuters	228.53	184.88	0.5986*	19,945*
Rio Tinto	74.344	66.019	0.6869	2,945.2
Royal & Sun Alliance Ins.	234.02	184.08	0.6832*	26,273*
Royal Bank of Scotland	188.40	174.17	0.7807	27,269
Sainsbury	65.492	63.919	0.6758	4,016.2
Scottish & Newcastle	124.25	116.41	0.9522	16,768
Standard Chartered	334.43	306.38	0.8899	134,077
Unilever	137.11	118.17*	0.7373	14,305

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 6.10. Best Forecast Model for the GARCH type and Stochastic Volatility Models (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
FTSE 100	SV	SV	SV	SV
Asda	SV	SV	SV	SV
Associated British Foods	SV	SV	SV	SV
BAA	ACGARCH	ACGARCH	GJR	ACGARCH
BAT Industries	ACGARCH	ACGARCH	ACGARCH	SV
BOC	GJR	GJR	GJR	SV
BG	GJR	GJR	GJR	GJR
BT	GJR	GJR	GJR	GJR
Barclays	SV	SV	SV	SV
Bass	GJR	GJR	GJR	GJR
Blue Circle	SV	SV	ACGARCH	ACGARCH
Boots	GJR	GJR	ACGARCH	ACGARCH
British Airways	GJR	GJR	GJR	GJR
CGU	GJR	GJR	GJR	GJR
Cadbury Schweppes	SV	SV	SV	SV
Diageo	GJR	GJR	GJR	GJR
EMI	GJR	GJR	GJR	ACGARCH
Enterprise Oil	GJR	GJR	GJR	SV
General Electric	ACGARCH	ACGARCH	SV	SV
Glaxo Wellcome	GJR	SV	SV	GJR
ICI	GJR	GJR	GJR	GJR
Ladbroke	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Land Securities	GJR	GJR	GJR	GJR
Legal & General	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Marks & Spencer	GJR	GJR	GJR	GJR
Natwest Bank	GJR	GJR	SV	SV
Pearson	GJR	GJR	GJR	GJR
Prudential	SV	SV	SV	SV

Table 6.10 (continued). Best Forecast Model for the GARCH type and Stochastic Volatility Models (Monthly Data)

Stock/Index	RMSE	MAE	MedAPE	MedSE
RMC	GJR	ACGARCH	ACGARCH	ACGARCH
Rank Group	GJR	GJR	GJR	GJR
Reckitt & Colman	GJR	SV	GJR	SV
Reed International	ACGARCH	GJR	GJR	GJR
Reuters	SV	SV	SV	SV
Rio Tinto	GJR	GJR	ACGARCH	ACGARCH
Royal & Sun Alliance Ins.	SV	SV	SV	SV
Royal Bank of Scotland	GJR	GJR	GJR	GJR
Sainsbury	GJR	GJR	GJR	GJR
Scottish & Newcastle	GJR	GJR	GJR	GJR
Standard Chartered	SV	SV	ACGARCH	GJR
Unilever	GJR	SV	ACGARCH	ACGARCH

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. GJR, ACGARCH and SV denote the GARCH/GJR, CGARCH/ACGARCH and stochastic volatility models respectively.

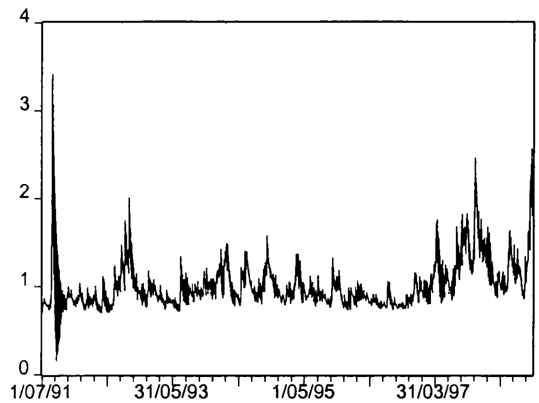
Table 6.11. Best Overall Forecast Model (Monthly Data)				
Stock/Index	**RMSE**	**MAE**	**MedAPE**	**MedSE**
FTSE 100	SV	SV	HM	HM
Asda	SV	SV	ES	SV
Associated British Foods	SV	SV	SV	SV
BAA	ES	ES	GJR	ES
BAT Industries	ACGARCH	ACGARCH	ACGARCH	HM
BOC	GJR	ES	ES	ES
BG	ES	ES	ES	ES
BT	ES	ES	ES	ES
Barclays	SV	SV	SV	SV
Bass	ES	ES	ES	ES
Blue Circle	ES	ES	ES	ES
Boots	HM	GJR	ACGARCH	ACGARCH
British Airways	GJR	GJR	GJR	GJR
CGU	GJR	GJR	GJR	GJR
Cadbury Schweppes	SV	SV	SV	ES
Diageo	ES	ES	ES	ES
EMI	GJR	ES	ES	ES
Enterprise Oil	GJR	GJR	GJR	HM
General Electric	ACGARCH	RW	RW	RW
Glaxo Wellcome	HM	HM	ES	HM
ICI	GJR	GJR	GJR	ES
Ladbroke	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Land Securities	GJR	GJR	GJR	GJR
Legal & General	ACGARCH	ACGARCH	HM	ACGARCH
Marks & Spencer	GJR	GJR	GJR	GJR
Natwest Bank	GJR	GJR	SV	SV
Pearson	RW	GJR	RW	GJR
Prudential	RW	ES	ES	ES
RMC	HM	HM	HM	ACGARCH

Table 6.11 (continued). Best Overall Forecast Model (Monthly Data)				
Stock/Index	**RMSE**	**MAE**	**MedAPE**	**MedSE**
Rank Group	GJR	GJR	GJR	GJR
Reckitt & Colman	GJR	HM	RW	HM
Reed International	ACGARCH	GJR	GJR	GJR
Reuters	ES	ES	SV	SV
Rio Tinto	ES	ES	ES	ES
Royal & Sun Alliance Ins.	RW	RW	SV	SV
Royal Bank of Scotland	HM	HM	HM	GJR
Sainsbury	RW	RW	ES	RW
Scottish & Newcastle	RW	RW	RW	RW
Standard Chartered	HM	HM	HM	ES
Unilever	GJR	SV	ACGARCH	ACGARCH

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999. GJR, ACGARCH, HM, RW and ES denote the GARCH/GJR, CGARCH/ACGARCH, historical mean, random walk and exponential smoothing models respectively.

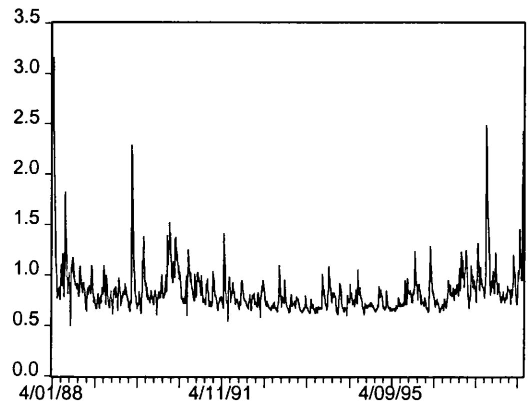
Appendix 6

Figure 7.1



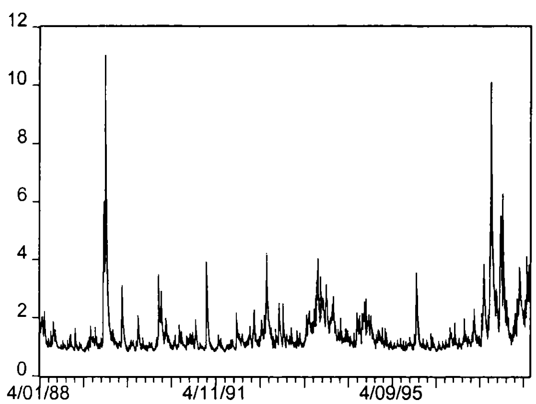
Germany (DAX)
Component model conditional standard deviation

Figure 7.2



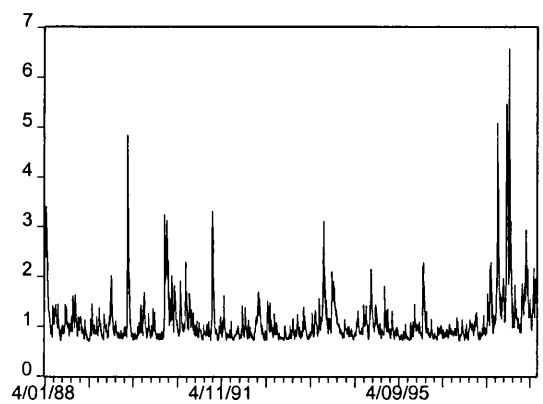
US (DJIA)
Asymmetric Component model conditional standard deviation

Figure 7.3



Hong Kong (Hang Seng)
Component model conditional standard deviation

Figure 7.4



Singapore (SST)
Component model conditional standard deviation

Table 7.1. Summary Statistics for the Index Returns

Index	Mean	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	JB
France (CAC 40)	0.0475	6.8079	-7.5735	1.1279	-0.1637	5.8060	926*
Germany (DAX)	0.0592	5.0760	-9.6277	1.0548	-0.6328	9.1653	3,095*
Japan (Nikkei 225)	-0.0243	7.6605	-6.1351	1.4016	0.2416	5.8991	720*
US (DJIA)	0.0479	4.6008	-7.4549	0.8702	-0.8627	11.361	8,458*
US (S&P 500)	0.0480	4.9887	-7.1127	0.8363	-0.8515	11.509	8,737*
US (NASDAQ)	0.0550	4.9347	-8.9536	0.8945	-0.9600	10.523	6,995*
Hong Kong (Hang Seng)	0.0453	17.247	-24.520	1.6848	-1.2337	30.702	89,754*
Singapore (SST)	0.0078	14.868	-10.207	1.2354	0.1804	19.966	33,415*
South Korea (KSE)	-0.0173	10.024	-11.601	1.6657	0.1487	8.4222	3,422*
Argentina (Merval)	-0.0063	12.072	-14.765	2.1794	-0.5134	7.5731	1,217*

Notes: The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, $JB \sim \chi_2^2$. An asterisk denotes significance in the JB statistic at the 5% level.

Table 7.2. GARCH/GJR Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero.

Index	μ	a_1	ω	α_1	β_1	γ_1
France (CAC 40)	0.0358 (0.0205)	0.0566* (0.0197)	0.0727* (0.0268)	0.0257* (0.0125)	0.8718* (0.0255)	0.0886* (0.0253)
Germany (DAX)	0.0636* (0.0237)	_	0.0528 (0.0410)	0.0800* (0.0173)	0.8739* (0.0432)	_
Japan (Nikkei 225)	-0.0353 (0.0255)	_	0.0320* (0.0153)	0.0111 (0.0110)	0.9225* (0.0158)	0.1061* (0.0249)
US (DJIA)	0.0455* (0.0146)	0.0416* (0.0189)	0.0221* (0.0065)	0.0135 (0.0112)	0.9214* (0.0145)	0.0675* (0.0239)
US (S&P 500)	0.0439* (0.0136)	0.0385* (0.0189)	0.0136* (0.0035)	0.0162 (0.0107)	0.9307* (0.0114)	0.0663* (0.0190)
US (NASDAQ)	0.0408* (0.0144)	0.2003* (0.0208)	0.0637* (0.0122)	0.0520* (0.0225)	0.7771* (0.0292)	0.1674* (0.0432)
Hong Kong (Hang Seng)	0.0610* (0.0223)	0.1385* (0.0236)	0.1036* (0.0309)	0.0466* (0.0207)	0.8257* (0.0253)	0.1722* (0.0458)
Singapore (SST)	0.0086 (0.0187)	0.2126* (0.0224)	0.0866 (0.0481)	0.0452* (0.0206)	0.8173* (0.0680)	0.1390* (0.0661)
South Korea (KSE)	-0.0188 (0.0240)	0.0417* (0.0207)	0.0657* (0.0198)	0.0733* (0.0179)	0.8620* (0.0199)	0.0828* (0.0293)
Argentina (Merval)	0.0323 (0.0459)	0.1372* (0.0318)	0.2108* (0.0574)	0.0305 (0.0283)	0.8266* (0.0365)	0.1762* (0.0560)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 7.3. GARCH/GJR Model Volatility Persistence Statistics

Index	Volatility Persistence	Half-life (days)	Wald ($\lambda = 1$)
France (CAC 40)	0.9419	11.57	8.2775*
Germany (DAX)	0.9538	14.66	1.7622
Japan (Nikkei 225)	0.9866	51.28	2.6017
US (DJIA)	0.9686	21.74	13.179*
US (S&P 500)	0.9800	34.37	11.668*
US (NASDAQ)	0.9128	7.60	27.886*
Hong Kong (Hang Seng)	0.9584	16.33	4.9766*
Singapore (SST)	0.9319	9.83	2.5309
South Korea (KSE)	0.9767	29.36	4.2521*
Argentina (Merval)	0.9452	12.30	12.840*

Notes: Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom. An asterisk denotes significance at the 5% level.

Table 7.4. GARCH/GJR Model Residual Diagnostics

Index	Mean	Standard Deviation	Skewness	Kurtosis	JB	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
France (CAC 40)	0.0077	1.1252	-0.1521	5.8003	920*	0.0055	6.6778	10.557	0.5647	0.8498	3.5960	0.5637	0.1650	0.3535
Germany (DAX)	0.0027	1.0798	-0.4804	7.8840	2,874*	0.3003	2.5047	4.0291	0.1845	0.6338	0.8743	0.1839	0.1233	0.0857
Japan (Nikkei 225)	0.0109	1.4016	0.2416	5.8991	720*	1.1147	1.7261	3.7567	0.2988	1.9253	6.6780	0.2996	0.3788	0.6752
US (DJIA)	0.0001	0.8705	-0.8152	11.312	8,322*	0.0960	6.2263	9.7082	0.0453	1.1830	2.0555	0.0452	0.2395	0.2050
US (S&P 500)	0.0019	0.8368	-0.8110	11.512	8,710*	0.0772	8.0600	11.733	0.0007	1.1857	2.4435	0.0007	0.2435	0.2481
US (NASDAQ)	0.0026	0.8850	-0.6283	10.713	7,083*	0.0738	1.3617	5.1704	0.0696	4.0289	5.1394	0.0695	0.8351	0.5177
Hong Kong (Hang Seng)	-0.0234	1.6975	-0.8608	31.388	93,828*	0.0047	11.680*	15.232	0.3839	2.2409	7.0746	0.3836	0.4503	0.6918
Singapore (SST)	-0.0043	1.2134	0.5728	21.469	39,721*	1.0680	2.6006	13.668	0.3170	0.9088	1.1435	0.3176	0.1783	0.1132
South Korea (KSE)	0.0026	1.6631	0.1575	8.5078	3,530*	1.0429	6.2951	13.631	0.0246	8.1109	47.969*	0.0247	1.6207	4.8219*
Argentina (Merval)	-0.0356	2.1660	-0.3477	7.2590	1,033*	0.1120	5.7856	8.7261	2.6048	7.5598	8.6883	2.5991	1.5154	0.8568

Notes: The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, $JB \sim \chi_2^2$. An asterisk denotes significance in the JB statistic at the 5% level. Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 7.5. CGARCH/ACGARCH Model Conditional Mean and Variance Specifications

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$
$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Index	μ	a_1	ω	ρ	ϕ	α	δ_s	β
Germany (DAX)	0.0580* (0.0270)	–	1.1501* (0.1926)	0.9483* (0.0143)	0.0785* (0.0198)	-0.0383* (0.0143)	–	-0.9298* (0.0100)
US (DJIA)	0.0448* (0.0002)	0.0505* (0.0195)	0.7477* (0.0847)	0.9083* (0.0472)	0.1773 (0.1725)	-0.2040 (0.1726)	0.1192* (0.0536)	0.9669* (0.2201)
US (NASDAQ)	0.0607* (0.0137)	0.1851* (0.0209)	0.8577* (0.2862)	0.9931* (0.0047)	0.0346* (0.0121)	0.1159* (0.0332)	–	0.6842* (0.0818)
Hong Kong (Hang Seng)	0.0905* (0.0218)	0.1344* (0.0268)	2.6845* (0.9118)	0.9662* (0.0192)	0.1366* (0.0251)	0.0515* (0.0244)	–	-0.8429* (0.0568)
Singapore (SST)	0.0320 (0.0181)	0.2145* (0.0229)	1.4176* (0.3351)	0.9351* (0.0410)	0.1533* (0.0502)	-0.0411 (0.0234)	–	-0.8695* (0.0856)
South Korea (KSE)	-0.0035 (0.0240)	0.0417* (0.0211)	2.1799* (0.5355)	0.9929* (0.0058)	0.0303 (0.0178)	0.0482 (0.0272)	0.0812* (0.0369)	0.8152* (0.0499)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 7.6. CGARCH/ACGARCH Model Volatility Persistence Statistics

Index	Permanent Component			Transitory Component			
	Volatility Persistence	Half-life (days)	Wald ($\lambda = 1$)	Volatility Persistence	Half-life (days)	Wald ($\alpha = \beta = 0$)	Wald ($\alpha + \delta_s = 0$)
Germany (DAX)	0.9483	13.06	13.115*	-0.9681	–	19.069*	–
US (DJIA)	0.9083	7.21	3.7742	0.8225	3.55	–	0.1675
US (NASDAQ)	0.9931	99.52	2.1818	0.8000	3.11	165.65*	–
Hong Kong (Hang Seng)	0.9662	20.14	3.1199	-0.7063	–	354.23*	–
Singapore (SST)	0.9351	10.32	2.5132	-0.9107	–	249.53*	–
South Korea (KSE)	0.9929	97.36	1.4893	0.9039	6.86	–	13.310*

Notes: Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom. An asterisk denotes significance at the 5% level.

Table 7.7. CGARCH/ACGARCH Model Residual Diagnostics

Index	Mean	Standard Deviation	Skewness	Kurtosis	JB	Q_1	Q_5	Q_{10}	Q_1^2	Q_5^2	Q_{10}^2	A_1	A_5	A_{10}
Germany (DAX)	0.0020	1.0550	-0.6328	9.1557	3,087*	0.2730	2.6305	4.7624	0.0570	0.3861	0.9546	0.0569	0.0763	0.0932
US (DJIA)	0.0003	0.8708	-0.8031	11.295	8,284*	0.1017	5.8549	9.7409	0.4578	2.3103	3.5475	0.4569	0.4763	0.3624
US (NASDAQ)	-0.0161	0.8844	-0.6611	10.681	7,050*	0.7168	1.6032	5.5838	0.0123	4.5220	6.1582	0.0122	0.9477	0.6339
Hong Kong (Hang Seng)	-0.0523	1.6964	-0.8738	31.385	93,853*	0.0016	12.096*	15.968	0.3280	1.7976	8.0734	0.3275	0.3546	0.7822
Singapore (SST)	-0.0273	1.2134	0.5757	21.477	39,769*	1.4807	3.0341	13.574	0.9805	1.3695	1.6587	0.9836	0.2683	0.1625
South Korea (KSE)	-0.0131	1.6628	0.1580	8.5096	3,534*	1.0588	4.3153	11.884	0.0594	7.3870	46.001*	0.0593	1.4833	4.5731

Notes: The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, $JB \sim \chi_2^2$. An asterisk denotes significance in the JB statistic at the 5% level. Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation, and Q_i^2 denotes the Ljung-Box test applied to the squares of the series, $Q_i^2 \sim \chi^2$ with degrees of freedom adjusted for ARMA parameter estimation. A_i denotes the i-th order Engle (1982) ARCH-LM test, $A_i \sim \chi_i^2$. An Asterisk denotes significance at the 5% level.

Table 7.8. Stochastic Volatility Conditional Mean and Variance Specifications

The following mean and variance specifications are used:

$$\ln(y_t^2) = \Lambda + h_t + \xi_t, \quad h_{t+1} = \Phi h_t + \eta_t$$

where $\Lambda = \ln(k^2) + E_t[\ln(\epsilon_t^2)]$ and $\ln(k^2) = \left(\frac{\delta}{1 - \Phi}\right)$.

Index	Λ	σ_ξ	Φ	σ_η	k^2
France (CAC 40)	-1.4437* (0.1237)	2.4839* (1.0000)	0.9821* (0.0049)	0.1093* (0.0044)	1.1587
Germany (DAX)	-1.6074* (0.2194)	2.3630* (1.0000)	0.9878* (0.0028)	0.1159* (0.0048)	0.9648
Japan (Nikkei 225)	-1.2188 (0.1344)	2.6280* (1.0000)	0.9634* (0.0136)	0.1997* (0.0119)	1.5689
US (DJIA)	-2.0468* (0.0883)	2.3619* (1.0000)	0.9863* (0.0050)	0.0561* (0.0016)	0.6686
US (S&P 500)	-1.9543* (0.4450)	2.4140* (1.0000)	0.9984* (0.0002)	0.0444* (0.0010)	0.7429
US (NASDAQ)	1.8611* (0.3611)	2.3772* (1.0000)	0.9973* (0.0007)	0.0560* (0.0013)	0.7564
Hong Kong (Hang Seng)	-1.1546* (0.2186)	2.5137* (1.0000)	0.9893* (0.0024)	0.1239* (0.0055)	1.8735
Singapore (SST)	-1.7968* (0.0973)	2.7178* (1.0000)	0.9196* (0.0357)	0.3510* (0.0304)	0.9443
South Korea (KSE)	-1.1327* (0.0897)	2.5918* (1.0000)	0.8146* (0.1131)	0.7354* (0.1434)	1.5861
Argentina (Merval)	-0.6095* (0.8918)	3.0814* (1.0000)	0.9745* (0.0083)	0.1953* (0.0104)	3.3249

Notes: Figures in parentheses are standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 7.9. Stochastic Volatility Model Residual Diagnostics

Stock/Index	Mean	S.D.	Skewness	Kurtosis	JB	Q_5	Q_{10}	Q_5^2	Q_{10}^2
France (CAC 40)	-0.0015	1.0000	-1.1810	4.9516	1,087*	3.6703	11.228	2.5434	7.3792
Germany (DAX)	0.0333	0.9994	-1.2266	5.7037	1,038*	1.8094	5.6031	1.2666	6.8480
Japan (Nikkei 225)	-0.0100	1.0000	-1.1665	4.2739	588*	1.6950	6.6035	10.824*	19.132*
US (DJIA)	-0.0292	0.9996	-1.0160	4.4700	764*	15.223*	23.348*	2.4798	5.5771
US (S&P 500)	-0.0036	1.0000	-1.2091	6.1718	1,843*	3.0239	8.5400	2.7038	4.5645
US (NASDAQ)	0.0134	0.9999	-1.1097	1.7357	920*	16.563*	20.347*	9.6043*	12.661
Hong Kong (Hang Seng)	0.0086	1.0000	-0.9762	4.2619	626*	10.074*	11.702	7.0480	10.536
Singapore (SST)	-0.0152	0.9999	-1.3348	5.2640	1,419*	5.2948	7.9538	17.416*	19.487*
South Korea (KSE)	0.0137	0.9999	-1.1335	4.3898	819*	2.3580	12.693	60.262*	63.459*
Argentina (Merval)	-0.0043	1.0000	-1.5710	5.4431	875*	5.4453	14.624	7.0156	10.249

Notes: S.D. denotes the standard deviation. The Jarque-Bera test for normality is calculated from the third and fourth moments of skewness and kurtosis, JB~χ_2^2. An asterisk denotes significance in the JB statistic at the 5% level. Q_i denotes the Ljung-Box statistic for serial correlation, $Q_i \sim \chi^2$ with (i - n + 1) degrees of freedom, where n is the number of hyperparameters. An asterisk denotes significance at the 5% level.

Table 7.10. GARCH/GJR Model Conditional Mean and Variance Specifications (Monday Effect)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise and $M_t = 1$ when the day of the week is Monday and zero otherwise. The GJR model reduces down to the GARCH model when γ_1 is restricted to zero.

Index	μ	a_1	λ_d	Wald ($\lambda_d = 0$)	ω	α_1	β_1	γ_1
France (CAC 40)	0.0771* (0.0212)	0.0571* (0.0196)	-0.2067* (0.0517)	15.972*	0.0680* (0.0260)	0.0272* (0.0124)	0.8744* (0.0249)	0.0877* (0.0251)
Japan (Nikkei 225)	0.0166* (0.0285)	–	-0.2571* (0.0803)	10.258*	0.0294* (0.0134)	0.0110 (0.0108)	0.9245* (0.0153)	0.1051* (0.0247)
US (NASDAQ)	0.0631* (0.0160)	0.1989* (0.0208)	-0.1066* (0.0354)	9.0412*	0.0562* (0.0110)	0.0566* (0.0221)	0.7926* (0.0274)	0.1478* (0.0412)
Hong Kong (Hang Seng)	0.1050* (0.0247)	0.1355* (0.0232)	-0.2157* (0.0770)	7.8472*	0.0994* (0.0287)	0.0484* (0.0199)	0.8269* (0.0248)	0.1704* (0.0453)
Singapore (SST)	0.0552* (0.0184)	0.2139* (0.0224)	-0.2220* (0.0584)	14.432*	0.0830 (0.0459)	0.0503* (0.0198)	0.8169* (0.0654)	0.8169* (0.0654)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes significance at the 5% level. Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom.

Table 7.11. CGARCH Model Conditional Mean and Variance Specifications (Monday Effect)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \quad h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$
$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Index	μ	a_1	λ_d	Wald ($\lambda_d = 0$)	ω	ρ	ϕ	α	β
US (NASDAQ)	0.0856* (0.0157)	0.1868* (0.0208)	-0.1308* (0.0354)	13.653*	0.8518* (0.2799)	0.9929* (0.0047)	0.0356* (0.0124)	0.1129* (0.0327)	0.6876* (0.0830)
Hong Kong (Hang Seng)	0.1330* (0.0250)	0.1317* (0.0263)	-0.2172* (0.0797)	7.4285*	2.7184* (0.9619)	0.9681* (0.0181)	0.1377* (0.0248)	0.0496* (0.0236)	-0.8480* (0.0543)
Singapore (SST)	0.0854* (0.0195)	0.2044* (0.0232)	-0.2342* (0.0602)	15.121*	1.3558* (0.3162)	0.9463* (0.0357)	0.1208* (0.0281)	0.0565 (0.0508)	0.5214 (0.8365)

Notes: Figures in parentheses are Bollerslev and Wooldridge (1992) robust standard errors. An asterisk denotes significance at the 5% level. Wald denotes the Wald test statistic, Wald~χ^2 with one degree of freedom.

Table 7.12. Stochastic Volatility Conditional Mean and Variance Specifications (Monday Effect)

The following mean and variance specifications are used:

$$\ln(y_t^2) = \Lambda + \lambda_d M_t + h_t + \xi_t, \quad h_{t+1} = \Phi h_t + \eta_t$$

where $\Lambda = \ln(k^2) + E_t[\ln(\epsilon_t^2)]$, $\ln(k^2) = \left(\frac{\delta}{1 - \Phi}\right)$ and $M_t = 1$ when the day of the week is Monday and zero otherwise.

Index	Λ	σ_ξ	Φ	σ_η	k^2	λ_d
US (DJIA)	-1.9974* (0.0894)	2.3595* (1.0000)	0.9849* (0.0056)	0.0601* (0.0018)	0.6661	-0.2565* (0.1118)
Singapore (SST)	-1.8653* (0.0996)	2.7116* (1.0000)	0.9156* (0.0384)	0.3633* (0.0325)	0.9402	0.3399* (0.1291)
South Korea (KSE)	-1.3192* (0.0928)	2.5531* (1.0000)	0.8087* (0.1191)	0.7602* (0.1576)	1.5790	0.9325* (0.1241)
Argentina (Merval)	-0.4891* (0.2254)	3.0719* (1.0000)	0.9740* (0.0086)	0.1982* (0.0107)	3.3232	-0.6024* (0.2108)

Notes: Figures in parentheses are standard errors. An asterisk denotes asymptotic coefficient significance at the 5% level.

Table 7.13. Log Likelihood Values for the Volatility Models

Index	GARCH	GJR	CGARCH	ACGARCH	SV
France (CAC 40)	-4163.254	-4149.465	–	–	-4,130.743
Germany (DAX)	-2624.679	–	-2635.660	–	-2,581.596
Japan (Nikkei 225)	-3373.002	-3342.078	–	–	-3,398.166
US (DJIA)	-3391.995	-3381.432	-3385.384	-3382.840	-3,456.402
US (S&P 500)	-3252.682	-3241.452	–	–	-3,252.540
US (NASDAQ)	-3349.381	-3328.204	-3333.688	–	3,405.334
Hong Kong (Hang Seng)	-4765.098	-4733.472	-4756.237	–	-5,066.845
Singapore (SST)	-4027.508	-4002.522	-4019.657	–	-3,859.991
South Korea (KSE)	-4875.278	-4872.653	-4875.327	-4870.537	-5,127.642
Argentina (Merval)	-2712.706	-2695.336	–	–	-3,423.048

Notes: The log likelihood values refer to the equation specifications shown in tables 7.2, 7.5 and 7.8. The log likelihood values for the stochastic volatility model are adjusted to make them comparable with the ARCH type models. The log likelihood transformation as proposed by Hansson and Hördahl (1998) is given by:

$$Lnl(t) = [-\ln(2\pi) - (h_t) - (y_t^2/\exp(h_t))]/2$$

where y_t is the mean adjusted return and h_t is the log-variance obtained from the Kalman filter.

Table 7.14. Schwarz Criterion Values for the Volatility Models

Index	GARCH	GJR	CGARCH	ACGARCH	SV
France (CAC 40)	3.005088	2.998031	–	–	2.977810
Germany (DAX)	2.819754	–	2.835487	–	2.769780
Japan (Nikkei 225)	3.386511	3.359401	–	–	3.411663
US (DJIA)	2.451023	2.446283	2.451971	2.452993	2.493548
US (S&P 500)	2.350942	2.345723	–	–	2.347148
US (NASDAQ)	2.420409	2.408045	2.414834	–	2.456875
Hong Kong (Hang Seng)	3.437447	3.417577	3.436780	–	3.650060
Singapore (SST)	2.907570	2.892469	2.907628	–	2.783379
South Korea (KSE)	3.522298	3.517563	3.522333	3.521741	3.693721
Argentina (Merval)	4.109386	4.088657	–	–	5.169073

Notes: The Schwarz criterion values refer to the equation specifications shown in tables 7.2, 7.5 and 7.8. The Schwarz criterion values for the stochastic volatility model are based on adjusted log likelihood values to make them comparable with the ARCH type models. The log likelihood transformation as proposed by Hansson and Hördahl (1998) is given by:

$$Lnl(t) = [-\ln(2\pi) - (h_t) - (y_t^2/\exp(h_t))]/2$$

where y_t is the mean adjusted return and h_t is the log-variance obtained from the Kalman filter.

Table 7.15. Forecast Error Statistics for the GARCH/GJR Model

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t, \quad h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise and $M_t = 1$ when the day of the week is Monday and zero otherwise. The GJR model reduces down to the GARCH model when $\gamma_1 = 0$.

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
France (CAC 40)	RMSE	10.601	8.2366*	2.9879*	4.0877	6.4762	2.2914
	MAE	7.8603	5.9083*	2.4367*	2.4141	3.5471	1.8389*
	MedAPE	1.1044	0.7474*	2.1350	2.5139	0.8108*	1.2769
	MedSE	23.370	19.038	3.4631	2.6157	2.7663	3.2631
Germany (DAX)	RMSE	15.291	12.313	3.2796	6.0851	7.8382	3.8339*
	MAE	9.0095	8.0095	2.7106	3.6503*	4.6430	2.2730
	MedAPE	0.7386	0.6734	0.6444	1.6500	0.8854*	1.3810
	MedSE	30.882	25.779*	6.1225	7.2641	7.4890	3.0464
Japan (Nikkei 225)	RMSE	6.7014	11.310*	3.9095*	2.5388*	2.5596	0.8469
	MAE	4.7076	7.2944	2.9706*	2.2890	2.0357	0.7753
	MedAPE	1.7665	0.9295	1.1632	5.0322	6.7464	2.2974
	MedSE	15.794	17.016	5.1505	4.5690	3.4292	0.6925
US (DJIA)	RMSE	5.5379*	3.5641	1.6428*	1.3362*	2.0982	1.3531*
	MAE	3.8918*	2.0834	0.9682*	1.1184*	1.4532*	0.9823*
	MedAPE	0.7658	4.1532	1.2780	2.7369	0.8039*	0.8274*
	MedSE	11.216	2.4644	0.3646*	0.9190*	0.8355*	0.6494
US (S&P 500)	RMSE	5.8076*	3.6307*	1.6083*	1.7571*	1.8496	2.1286
	MAE	4.3494*	2.4450	0.9523*	1.4508*	1.3829*	1.5904*
	MedAPE	0.7476*	2.4290	1.8113	1.6310*	1.3611	0.7784
	MedSE	12.226	3.5986	0.3456	1.2901*	0.7449*	1.0005*
US (NASDAQ)	RMSE	9.7103*	5.5321*	2.8740*	2.8790*	3.6525	5.9891
	MAE	6.7950	3.6066*	1.4091*	2.3453*	2.7952*	4.9116
	MedAPE	1.2314	0.6749*	0.8851	0.6909	1.1053	0.8543*
	MedSE	13.157	5.1995*	0.4012*	4.2414*	4.3533	17.983

Table 7.15 (continued). Forecast Error Statistics for the GARCH/GJR Model.

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Hong Kong (Hang Seng)	RMSE	6.9051*	19.277	4.8937	6.1318	6.1841	4.2928
	MAE	6.2366	9.9460*	3.8967*	4.5344*	4.4208*	3.6866
	MedAPE	1.7136	1.4318*	0.7925	2.2824	2.2363	5.7224
	MedSE	27.797*	14.178	8.7094*	15.197	8.3094*	12.737
Singapore (SST)	RMSE	5.7543*	18.119	8.4401	3.5124	9.7047	6.5084
	MAE	4.1923*	9.5449	5.4496*	2.9424	5.0071*	3.9123
	MedAPE	0.7487	0.8130	0.5954*	1.8235	0.8339*	0.9671
	MedSE	11.023	36.317	11.308*	5.2553	3.5828*	8.4758
South Korea (KSE)	RMSE	10.703	17.704	8.0603*	27.028	10.144	10.172*
	MAE	6.7479	11.853	6.5110	16.718	7.9558	7.8416
	MedAPE	2.4023	1.0020	5.2684	1.5385	1.4991	3.6097
	MedSE	17.231	47.450	29.052	113.07	33.437	44.828
Argentina (Merval)	RMSE	46.838*	15.250	8.8494*	13.052	36.805*	7.9289
	MAE	27.059*	10.623*	5.6121*	9.1819	20.067	6.1309
	MedAPE	0.8259	1.0223	1.4342	3.5844	2.8592	7.2705
	MedSE	289.24	65.574	10.247	49.167	53.573	18.442

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 7.16. Forecast Error Statistics for the CGARCH/ACGARCH Model

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t, \; h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$

$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Germany (DAX)	RMSE	15.207	12.030*	3.2634*	6.3001	7.8985	3.9365
	MAE	8.6770*	7.9223*	2.4324*	3.7881	4.7440	2.1767*
	MedAPE	0.7261*	0.6482*	0.6011*	1.1040	1.1065	0.9545
	MedSE	19.581*	26.825	4.9237*	6.7014*	7.4148	1.4275
US (DJIA)	RMSE	5.7430	3.6704	1.7076	1.3708	2.0616	1.3590
	MAE	3.8990	2.4795	1.3029	1.2203	1.4915	1.0216
	MedAPE	0.8040	5.5445	3.0860	3.6499	0.8915	0.9083
	MedSE	8.6529	4.3396	1.1708	1.3680	1.2158	0.7122
US (NASDAQ)	RMSE	10.235	6.1193	2.9157	3.0020	3.4660*	5.9135
	MAE	7.4047	4.5259	2.0588	2.5116	2.8284	4.8464
	MedAPE	1.5300	1.0172	2.6079	0.6163	1.5598	0.9556
	MedSE	21.148	15.177	1.9406	6.7747	4.3189*	17.039
Hong Kong (Hang Seng)	RMSE	7.7929	19.508	4.9503	6.1949	6.0884	4.0201
	MAE	6.8220	12.174	4.2099	4.6327	4.6455	3.4146
	MedAPE	1.6122	3.5202	0.9811	2.1436	2.4157	4.5840
	MedSE	37.112	44.751	12.915	13.844	12.560	12.020
Singapore (SST)	RMSE	6.1354	17.990	8.7099	3.3632*	9.7186	6.6961
	MAE	4.7395	10.389	5.8828	2.7635*	5.2290	3.9145
	MedAPE	0.9448	0.8687	0.6775	1.4693	0.9341	0.7952
	MedSE	15.971	49.336	14.352	4.6803*	7.0783	6.6694
South Korea (KSE)	RMSE	10.628	17.530	8.3191	26.611	9.8772*	10.253
	MAE	6.9780	12.204	7.2521	16.829	8.3144	7.7333
	MedAPE	3.0386	1.2696	7.4263	2.2733	1.9896	3.4348
	MedSE	16.654	55.535	47.451	139.76	45.770	42.519

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 7.17. Forecast Error Statistics for the Stochastic Volatility Model

The one-step ahead forecast of the conditional variance is given by:

$$h_{t+1} = k^2 \exp(h_{t|T})^{\Phi}$$

where $\exp(h_{t|T})$ is the smoothed estimate of the volatility process.

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
France (CAC 40)	RMSE	11.152	9.7541	3.0293	4.0110*	6.5154	2.2709*
	MAE	7.2352*	5.9891	2.5702	2.3528*	3.4604*	1.8729
	MedAPE	0.8770*	0.8889	2.1401	1.9562	0.8381	0.9103*
	MedSE	7.8893*	6.8356*	4.2541	2.6023	1.6682*	3.7791
Germany (DAX)	RMSE	14.949	12.417	4.1271	6.0088*	7.9807	3.8927
	MAE	8.7740	8.3773	3.5537	4.0005	4.5772*	2.8014
	MedAPE	0.7918	0.7136	1.2270	2.0570	0.9119	2.3967
	MedSE	24.879	31.943	15.373	9.7936	4.5574*	6.0646
Japan (Nikkei 225)	RMSE	6.6225	11.797	4.1317	2.5475	2.6213	1.0555
	MAE	4.1987*	6.6351*	3.1580	2.3461	1.7594*	0.9355
	MedAPE	0.8467*	0.9113*	1.0792	5.8588	2.9033	2.9725
	MedSE	6.4841*	11.851*	6.3554	5.3675	1.2125	1.1681
US (DJIA)	RMSE	6.2873	3.5285*	1.7532	1.4313	2.0164*	1.3783
	MAE	4.1170	2.0426*	1.4848	1.3141	1.4968	1.1289
	MedAPE	0.8974	3.9838	3.9003	4.0561	0.8486	1.1529
	MEDSE	3.3366*	3.3539	2.1695	1.8140	1.5673	1.2084
US (S&P 500)	RMSE	6.5631	3.6328	1.9723	1.8127	1.8030*	2.2728
	MAE	4.4402	2.3362*	1.8338	1.6726	1.5010	1.7842
	MedAPE	0.8197	3.0520	4.7751	2.8463	1.8011	1.0066
	MedSE	4.8341*	3.6949	3.3709	2.8957	1.7963	1.8473
US (NASDAQ)	RMSE	10.390	6.9365	4.1059	3.1367	3.4953	5.9097
	MAE	6.6981*	5.4153	3.7548	2.6889	2.9036	4.6149
	MedAPE	0.8897*	1.0872	7.1783	0.5853*	2.1036	1.0017
	MedSE	9.8240*	23.542	11.792	10.279	5.9717	10.980*

Table 7.17 (continued). Forecast Error Statistics for the Stochastic Volatility Model.

Stock/Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Hong Kong (Hang Seng)	RMSE	7.9782	18.751*	4.8432*	6.0368*	5.9300	4.2716
	MAE	7.4324	10.191	3.9409	4.7542	4.6620	3.6268
	MedAPE	2.7585	1.8434	0.7519*	1.7962	2.8289	3.8135
	MedSE	64.158	23.821	14.464	13.897	11.103	14.826
Singapore (SST)	RMSE	5.8960	18.086	9.4887	3.7837	9.9402	6.1482*
	MAE	4.2558	9.2261*	6.1195	3.1709	5.3546	3.5660*
	MedAPE	0.7128	0.8187	0.8576	2.2994	0.8935	0.6646*
	MedSE	9.4611*	23.949*	11.360	10.209	4.8816	5.3072*
South Korea (KSE)	RMSE	10.673	18.843	8.2873	27.752	10.672	10.827
	MAE	5.7142*	11.150*	5.7016*	15.122*	6.7209*	6.9166*
	MedAPE	1.3972	0.9654	3.2090	0.9184*	0.9507*	1.0238*
	MedSE	9.1356*	12.327*	9.8682*	30.162*	9.1725	17.583
Argentina (Merval)	RMSE	50.283	15.142*	9.8442	12.508*	39.906	6.1906*
	MAE	27.725	10.670	8.0619	6.5625*	17.639*	3.9350*
	MedAPE	0.7591*	1.9459	4.2389	1.3228	0.8857*	4.2589
	MedSE	243.62*	71.775	56.169	12.110*	17.214	9.3530

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 7.18. Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

The historical mean volatility forecast is expressed as:

$$h_{t+1} = \bar{s}_t^2 = \frac{1}{t}\sum_{j=1}^{t} s_j^2$$

where s_t^2 is the true volatility.

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
France (CAC 40)	RMSE	10.786	9.2070	4.9903	5.0092	6.0380*	3.2906
	MAE	9.1601	8.0180	4.4371	4.6463	4.3677	3.0809
	MedAPE	2.1690	3.0786	11.061	6.3984	1.9817	2.9413
	MedSE	49.401	56.172	29.708	22.186	13.806	11.515
Germany (DAX)	RMSE	15.144	12.663	6.2327	6.9847	7.5467*	5.3934
	MAE	9.8424	9.7457	5.6038	6.0578	6.0606	5.1183
	MedAPE	0.8730	1.0128	2.4040	4.6667	2.3014	5.1243
	MedSE	55.380	58.749	37.309	36.339	30.652	25.765
Japan (Nikkei 225)	RMSE	7.2412	11.426	4.6969	3.8206	3.3651	2.7508
	MAE	4.6986	7.5025	4.1758	3.6618	3.1226	2.6830
	MedAPE	1.0420	1.0134	2.5814	9.9379	13.122	7.7087
	MedSE	17.352	26.809	18.227	15.951	12.496	8.5065
US (DJIA)	RMSE	6.7345	4.1696	2.3677	1.7777	2.0482	1.5305
	MAE	5.5296	3.4633	2.2969	1.6222	1.7114	1.3763
	MedAPE	4.6179	8.7307	7.0025	6.2993	1.4751	1.8531
	MedSE	23.566	11.252	5.9124	4.2163	3.2831	1.8347
US (S&P 500)	RMSE	7.1565	4.2253	2.5402	1.9687	1.9458	2.0299*
	MAE	5.7797	3.6238	2.4850	1.8241	1.8074	1.7310
	MedAPE	1.7171	5.6867	7.5705	3.6918	2.9573	1.1807
	MedSE	29.494	11.009	6.2046	4.8506	3.6281	2.5284
US (NASDAQ)	RMSE	11.244	6.8148	4.8472	3.2646	3.6717	5.5357*
	MAE	8.8790	5.9093	4.6594	2.7816	3.4336	4.5137*
	MedAPE	5.5264	1.4643	10.380	0.6185	4.5163	1.1770
	MedSE	44.093	27.418	23.501	10.007	14.808	15.497

Table 7.18 (continued). Forecast Error Statistics for the Historical Mean Model (Recursive Equation Estimation)

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Hong Kong (Hang Seng)	RMSE	6.9741	19.121	5.3465	6.5356	5.9280*	4.6630
	MAE	6.2301*	11.932	4.7666	6.0530	5.0392	4.3417
	MedAPE	0.9637	3.0275	2.4634	2.9868	4.6670	5.4325
	MedSE	35.556	63.610	27.812	33.988	24.942	22.107
Singapore (SST)	RMSE	6.0980	17.471*	8.2838*	5.1634	9.2193	6.4263
	MAE	4.9234	9.3740	6.2963	4.8065	6.7090	4.6669
	MedAPE	0.6917*	0.7541*	0.7618	5.4594	2.6135	1.6810
	MedSE	22.997	35.550	29.910	32.780	34.182	14.734
South Korea (KSE)	RMSE	11.272	17.394*	8.2587	26.382*	9.9441	10.245
	MAE	7.6361	11.886	7.6565	15.577	8.9083	8.1708
	MedAPE	1.5572	1.5526	9.8286	2.1148	2.0614	4.4528
	MedSE	35.441	50.132	59.491	69.037	68.218	71.007
Argentina (Merval)	RMSE	53.711	22.149	15.448	14.569	37.528	12.017
	MAE	38.287	20.495	14.771	13.458	21.136	11.836
	MedAPE	1.4578	5.9228	11.119	7.1819	6.3207	20.457
	MedSE	879.59	478.28	254.78	183.67	147.56	156.24

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 7.19. Forecast Error Statistics for the Random Walk Model

The random walk volatility forecast is expressed as:

$$h_{t+1} = s_t^2$$

where s_t^2 is the true volatility for period t.

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
France (CAC 40)	RMSE	15.696	11.289	3.4534	4.8949	9.1975	3.3114
	MAE	12.358	7.5003	2.4422	2.7641	5.9360	2.2439
	MedAPE	1.0000	0.9834	1.7204*	0.9385*	0.9291	0.9588
	MedSE	103.59	28.510	2.0939*	1.6884*	7.7564	1.9083*
Germany (DAX)	RMSE	21.399	18.523	4.5764	8.1580	11.808	5.2912
	MAE	14.598	12.654	3.5204	5.3483	8.1776	2.4276
	MedAPE	0.9981	0.9992	0.9795	0.9884*	1.0314	0.9326*
	MedSE	62.816	47.778	6.1564	11.969	34.756	0.2775*
Japan (Nikkei 225)	RMSE	9.4900	13.776	6.3573	3.0895	3.6134	0.9534
	MAE	6.5964	8.5706	4.2797	1.9162*	2.2581	0.7868
	MedAPE	2.1761	0.9931	0.9648*	0.8536*	0.9986*	0.9461*
	MedSE	24.812	17.925	3.4675*	0.1277*	1.1339*	0.8383
US (DJIA)	RMSE	6.5367	4.9931	2.0021	2.3132	2.4889	1.8516
	MAE	4.7048	2.3935	1.2539	1.7011	1.7820	1.2780
	MedAPE	0.9827	1.0690*	0.9980*	1.0200*	0.9745	0.9599
	MedSE	13.451	0.5716*	0.4736	1.9102	1.0867	0.5694*
US (S&P 500)	RMSE	7.0048	5.2181	1.8835	2.7906	2.5529	3.0275
	MAE	4.6589	2.7088	1.1208	2.2781	1.9258	2.4029
	MedAPE	0.9779	0.9809*	0.9697*	2.9258	0.9892*	0.9974
	MedSE	16.413	0.6758*	0.1803*	4.0642	2.6353	2.8742
US (NASDAQ)	RMSE	12.303	9.0723	3.0743	4.2007	5.3768	8.5649
	MAE	8.3465	6.1906	1.8562	3.4846	4.2998	6.9328
	MedAPE	0.9781	0.8890	0.8725*	0.9731	0.9917*	0.9887
	MedSE	31.930	6.7062	0.4872	8.4835	18.008	36.169

Table 7.19 (continued). Forecast Error Statistics for the Random Walk Model							
Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Hong Kong (Hang Seng)	RMSE	9.8895	25.717	6.9343	8.5220	8.1082	5.4234
	MAE	8.2923	13.978	5.5094	5.1728	5.6758	3.9355
	MedAPE	0.9558*	1.4473	0.9808	0.9867*	0.9849*	0.9992*
	MedSE	114.43	12.770*	36.974	2.4231*	17.537	6.9232*
Singapore (SST)	RMSE	8.2267	23.835	10.621	5.1683	10.872	11.226
	MAE	5.7125	13.028	8.1510	3.8953	6.4613	6.1484
	MedAPE	0.9656	0.9664	0.9928	0.9213*	0.9816	0.8605
	MedSE	11.477	42.831	56.883	10.118	6.0534	6.8909
South Korea (KSE)	RMSE	14.762	20.295	12.866	37.013	12.647	15.407
	MAE	8.7818	13.021	9.2057	24.437	8.4545	9.2125
	MedAPE	0.9989*	0.9321*	1.1359*	1.7959	0.9875	0.9790
	MedSE	17.744	59.967	31.153	123.04	6.8931*	5.9235*
Argentina (Merval)	RMSE	63.687	22.407	10.980	19.160	51.473	9.0497
	MAE	42.262	14.477	6.7651	11.716	27.581	4.9612
	MedAPE	0.9830	1.0043*	1.1527*	1.2926*	0.9317	0.9945*
	MedSE	545.71	36.927*	5.2297*	12.742	7.5571*	7.7741*

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 7.20. Forecast Error Statistics for the Exponential smoothing Model

The exponential smoothing volatility forecast is expressed as:

$$h_{t+1} = \phi_T h_t + (1 - \phi_T) s_t^2$$

where ϕ is the smoothing parameter and s_t^2 is the true volatility.

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
France (CAC 40)	RMSE	10.383*	9.0767	3.3260	4.0987	6.3224	2.4422
	MAE	7.8230	7.6282	3.0191	2.8153	3.7179	2.1290
	MedAPE	0.9944	2.2997	4.8789	3.2295	1.0618	1.6583
	MedSE	26.251	40.029	8.4194	5.2287	3.3690	5.0799
Germany (DAX)	RMSE	14.908*	12.718	4.2153	6.0996	7.6904	4.0414
	MAE	9.0895	9.5695	3.6109	4.2182	4.9396	2.8689
	MedAPE	0.7764	0.9520	1.3299	2.3531	1.3207	2.2103
	MedSE	40.113	46.099	15.238	13.452	12.391	6.6952
Japan (Nikkei 225)	RMSE	6.5003*	11.483	4.2638	2.5739	2.5361*	0.8146*
	MAE	4.4641	7.7336	3.6387	2.3451	1.9081	0.7496*
	MedAPE	1.3655	1.0799	1.9864	5.0769	5.9728	1.9070
	MedSE	12.470	21.466	10.266	4.3898	2.3974	0.5600*
US (DJIA)	RMSE	5.8445	3.8777	2.0528	1.4674	2.0296	1.3727
	MAE	4.0693	2.9969	1.8928	1.3510	1.5291	1.0847
	MedAPE	0.7597*	7.2889	5.5132	4.5386	0.9585	1.1585
	MedSE	13.265	8.1351	3.5985	2.2533	1.4861	0.9840
US (S&P 500)	RMSE	6.1172	3.9760	2.0921	1.7827	1.8266	2.0761
	MAE	4.5065	3.1973	1.9367	1.6225	1.5240	1.6389
	MedAPE	0.7831	4.8830	5.9124	2.5042	1.8230	0.7470*
	MedSE	15.478	7.9933	3.0789	2.6659	1.9268	1.5136
US (NASDAQ)	RMSE	9.8601	6.6282	3.2894	2.9809	3.4927	5.7494
	MAE	7.6048	5.6803	2.4980	2.5126	2.9337	4.6942
	MedAPE	2.1311	1.3693	3.4733	0.6986	2.1278	1.0806
	MedSE	39.300	23.059	3.4813	6.2516	6.4594	14.802

Table 7.20 (continued). Forecast Error Statistics for the Exponential smoothing Model

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Hong Kong (Hang Seng)	RMSE	7.7732	19.194	4.9372	6.0863	5.9940	3.9325*
	MAE	6.8616	13.069	4.5143	4.9020	4.6503	3.3304*
	MedAPE	2.2666	3.7448	1.9571	2.1582	2.8369	4.2818
	MedSE	56.544	72.813	20.463	15.381	11.527	11.292
Singapore (SST)	RMSE	5.8511	17.688	8.3904	3.7136	9.4977*	6.4519
	MAE	4.7456	10.275	6.4920	3.3375	5.4394	4.2126
	MedAPE	0.8015	0.8163	0.8623	3.2130	0.9249	1.3030
	MedSE	21.481	41.976	32.693	15.441	7.2883	9.4604
South Korea (KSE)	RMSE	10.530*	17.531	8.3038	26.675	10.437	10.329
	MAE	7.0226	12.396	7.5155	17.032	9.2394	8.0681
	MedAPE	2.6583	1.7675	8.7342	2.1609	2.0553	4.0373
	MedSE	27.987	67.532	53.078	124.61	53.550	56.253
Argentina (Merval)	RMSE	47.505	17.039	9.0431	12.720	38.604	9.9776
	MAE	29.896	14.169	6.8148	8.3253	21.169	8.3603
	MedAPE	0.9843	3.2368	3.3297	2.8452	2.8739	12.396
	MedSE	489.85	158.91	27.298	34.531	49.421	61.191

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for the given forecast sample and forecast error statistic.

Table 7.21. Best Forecast Model for the GARCH type and Stochastic Volatility Models

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
France (CAC 40)	RMSE	GJR	GJR	GJR	SV	GJR	SV
	MAE	SV	GJR	GJR	SV	SV	GJR
	MedAPE	SV	GJR	GJR	SV	GJR	SV
	MedSE	SV	SV	GJR	SV	SV	GJR
Germany (DAX)	RMSE	SV	ACGARCH	ACGARCH	SV	GJR	GJR
	MAE	ACGARCH	ACGARCH	ACGARCH	GJR	SV	ACGARCH
	MedAPE	ACGARCH	ACGARCH	ACGARCH	ACGARCH	GJR	ACGARCH
	MedSE	ACGARCH	GJR	ACGARCH	ACGARCH	SV	ACGARCH
Japan (Nikkei 225)	RMSE	SV	GJR	GJR	GJR	GJR	GJR
	MAE	SV	SV	GJR	GJR	SV	GJR
	MedAPE	SV	SV	SV	GJR	SV	GJR
	MedSE	SV	SV	GJR	GJR	SV	GJR
US (DJIA)	RMSE	GJR	SV	GJR	GJR	SV	GJR
	MAE	GJR	SV	GJR	GJR	GJR	GJR
	MedAPE	GJR	SV	GJR	GJR	GJR	GJR
	MedSE	SV	GJR	GJR	GJR	GJR	GJR
US (S&P 500)	RMSE	GJR	GJR	GJR	GJR	SV	GJR
	MAE	GJR	SV	GJR	GJR	GJR	GJR
	MedAPE	GJR	GJR	GJR	GJR	GJR	GJR
	MedSE	SV	GJR	GJR	GJR	GJR	GJR
US (NASDAQ)	RMSE	GJR	GJR	GJR	GJR	ACGARCH	SV
	MAE	SV	GJR	GJR	GJR	GJR	SV
	MedAPE	SV	GJR	GJR	SV	GJR	GJR
	MedSE	SV	GJR	GJR	GJR	ACGARCH	SV
Hong Kong (Hang Seng)	RMSE	GJR	SV	SV	SV	SV	ACGARCH
	MAE	GJR	GJR	GJR	GJR	GJR	ACGARCH
	MedAPE	ACGARCH	GJR	SV	SV	GJR	SV
	MedSE	GJR	GJR	GJR	ACGARCH	GJR	ACGARCH

Table 7.21 (continued). Best Forecast Model for the GARCH type and Stochastic Volatility Models

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Singapore (SST)	RMSE	GJR	ACGARCH	GJR	ACGARCH	GJR	SV
	MAE	GJR	SV	GJR	ACGARCH	GJR	SV
	MedAPE	SV	GJR	GJR	ACGARCH	GJR	SV
	MedSE	SV	SV	GJR	ACGARCH	GJR	SV
South Korea (KSE)	RMSE	ACGARCH	ACGARCH	GJR	ACGARCH	ACGARCH	GJR
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	SV	SV	SV	SV	SV	SV
	MedSE	SV	SV	SV	SV	SV	SV
Argentina (Merval)	RMSE	GJR	SV	GJR	SV	GJR	SV
	MAE	GJR	GJR	GJR	SV	SV	SV
	MedAPE	SV	GJR	GJR	SV	SV	SV
	MedSE	SV	GJR	GJR	SV	SV	SV

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. GJR, ACGARCH and SV denote the GARCH/GJR and CGARCH/ACGARCH models respectively.

Table 7.22. Best Forecast Model Overall

Index		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
France (CAC 40)	RMSE	ES	GJR	GJR	SV	HM	SV
	MAE	SV	GJR	GJR	SV	SV	GJR
	MedAPE	SV	GJR	RW	RW	GJR	SV
	MedSE	SV	SV	RW	RW	SV	RW
Germany (DAX)	RMSE	ES	ACGARCH	ACGARCH	SV	HM	GJR
	MAE	ACGARCH	ACGARCH	ACGARCH	GJR	SV	ACGARCH
	MedAPE	ACGARCH	ACGARCH	ACGARCH	RW	GJR	RW
	MedSE	ACGARCH	GJR	ACGARCH	ACGARCH	SV	RW
Japan (Nikkei 225)	RMSE	ES	GJR	GJR	GJR	ES	ES
	MAE	SV	SV	GJR	RW	SV	ES
	MedAPE	SV	SV	RW	RW	RW	RW
	MedSE	SV	SV	RW	RW	RW	ES
US (DJIA)	RMSE	GJR	SV	GJR	GJR	SV	GJR
	MAE	GJR	SV	GJR	GJR	GJR	GJR
	MedAPE	ES	RW	RW	RW	GJR	GJR
	MedSE	SV	RW	GJR	GJR	GJR	RW
US (S&P 500)	RMSE	GJR	GJR	GJR	GJR	SV	HM
	MAE	GJR	SV	GJR	GJR	GJR	GJR
	MedAPE	GJR	RW	RW	GJR	RW	ES
	MedSE	SV	RW	RW	GJR	GJR	GJR
US (NASDAQ)	RMSE	GJR	GJR	GJR	GJR	ACGARCH	HM
	MAE	SV	GJR	GJR	GJR	GJR	HM
	MedAPE	SV	GJR	RW	SV	RW	GJR
	MedSE	SV	GJR	GJR	GJR	ACGARCH	SV
Hong Kong (Hang Seng)	RMSE	GJR	SV	SV	SV	HM	ES
	MAE	HM	GJR	GJR	GJR	GJR	ES
	MedAPE	RW	GJR	SV	RW	RW	RW
	MedSE	GJR	RW	GJR	RW	GJR	RW

Table 7.22 (continued). Best Forecast Model Overall							
Index		**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Singapore (SST)	RMSE	GJR	HM	HM	ACGARCH	ES	SV
	MAE	GJR	SV	GJR	ACGARCH	GJR	SV
	MedAPE	HM	HM	GJR	RW	GJR	SV
	MedSE	SV	SV	GJR	ACGARCH	GJR	SV
South Korea (KSE)	RMSE	ES	HM	GJR	HM	ACGARCH	GJR
	MAE	SV	SV	SV	SV	SV	SV
	MedAPE	RW	RW	RW	SV	SV	SV
	MedSE	SV	SV	SV	SV	RW	RW
Argentina (Merval)	RMSE	GJR	SV	GJR	SV	GJR	SV
	MAE	GJR	GJR	GJR	SV	SV	SV
	MedAPE	SV	RW	RW	RW	SV	RW
	MedSE	SV	RW	RW	SV	RW	RW

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). Samples 1 to 6 refer to the forecast periods 8/9/1998 to 5/10/1998, 6/10/1998 to 2/11/1998, 3/11/1998 to 30/11/1998, 1/12/1998 to 28/12/1998, 29/12/1998 to 25/1/1999 and 26/1/1999 to 22/2/1999 respectively. GJR, ACGARCH, SV, HM, RW and ES denote the GARCH/GJR, CGARCH/ACGARCH, stochastic volatility, historical mean, random walk and exponential smoothing models respectively.

Table 7.23. Forecast Error Statistics for the GARCH/GJR Model (Monthly Data)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \lambda_d M_t + \epsilon_t,$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 \epsilon_{t-1}^2 D_{t-1}$$

where $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise and $M_t = 1$ when the day of the week is Monday and zero otherwise. The GJR model reduces down to the GARCH model when $\gamma_1 = 0$.

Index	RMSE	MAE	MedAPE	MedSE
France (CAC40)	65.014	45.476	0.3819	1,821.7
Germany (DAX)	85.681	70.742*	0.7175	3,616.0
Japan (Nikkei 225)	29.346*	25.756	0.5329	561.57
US (DJIA)	25.447	16.845	0.3811	151.12
US (S&P 500	27.901	25.955	0.6682	611.96
US (NASDAQ)	47.979*	42.931	0.5052	1,808.0
Hong Kong (Hang Seng)	146.07	110.82	0.8345	3,846.4
Singapore (SST)	124.28	110.65	0.9252	12,989
South Korea (KSE)	71.981*	57.865*	0.3310*	2,124.7*
Argentina (Merval)	130.39*	113.76*	0.4846*	12,995

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 7.24. Forecast Error Statistics for the CGARCH/ACGARCH Model (Monthly Data)

The following mean and variance equation specifications are used:

$$r_t = \mu + a_1 r_{t-1} + \epsilon_t$$
$$h_t = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \delta_s(D_{t-1}\epsilon_{t-1}^2 - 0.5q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$
$$q_t = \omega + \rho q_{t-1} + \phi(\epsilon_{t-1}^2 - h_{t-1})$$

where q_t is the permanent component of the conditional variance and $D_{t-1} = 1$ when ϵ_{t-1} is negative and zero otherwise. The ACGARCH model reduces down to the CGARCH model when δ_s is restricted to zero.

Index	RMSE	MAE	MedAPE	MedSE
France (CAC40)	57.111*	38.644*	0.3553*	675.13*
Japan (Nikkei 225)	43.440	36.476	0.6939	1,154.5
US (DJIA)	11.284*	10.782*	0.3651*	130.95*
US (S&P 500	34.694	31.835	0.7162	743.38
US (NASDAQ)	56.791	52.503	0.5253	3,561.3
Hong Kong (Hang Seng)	145.43	120.38	1.2291	9,799.6

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 7.25. Forecast Error Statistics for the Stochastic Volatility Model (Monthly Data)

The one-step ahead forecast of the conditional variance is given by:

$$h_{t+1} = k^2 \exp(h_{t|T})^{\Phi}$$

where $\exp(h_{t|T})$ is the smoothed estimate of the volatility process.

Index	RMSE	MAE	MedAPE	MedSE
France (CAC40)	86.764	69.348	0.8702	3,410.2
Germany (DAX)	83.875*	71.751	0.5528*	5,023.3
Japan (Nikkei 225)	67.935	54.187	0.8173	1,786.6
US (DJIA)	33.949	27.043	0.8069	607.16
US (S&P 500	25.407*	20.689*	0.4314	238.29
US (NASDAQ)	50.147	41.788*	0.5871	1,402.7*
Hong Kong (Hang Seng)	110.22	83.548	0.9315	3,878.1
Singapore (SST)	89.717	76.558	0.5880*	3,668.9*
South Korea (KSE)	122.56	88.396	0.4666	3,212.9
Argentina (Merval)	223.59	166.87	0.6387	15,421

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 7.26. Forecast Error Statistics for the Historical Mean Model (Monthly Data)

The historical mean volatility forecast is expressed as:

$$h_{t+1} = \bar{s}_t^2 = \frac{1}{t}\sum_{j=1}^{t} s_j^2$$

where s_t^2 is the true volatility.

Index	RMSE	MAE	MedAPE	MedSE
France (CAC40)	69.349	49.644	0.4199	1,187.8
Germany (DAX)	102.84	79.250	0.5966	2,845.4*
Japan (Nikkei 225)	50.754	37.877	0.5078	561.34
US (DJIA)	33.455	21.486	0.4247	160.60
US (S&P 500	37.818	27.790	0.5905	425.19
US (NASDAQ)	67.035	54.413	0.6036	2,878.1
Hong Kong (Hang Seng)	57.768*	41.942*	0.3042*	534.10*
Singapore (SST)	87.023*	71.612*	0.6004	4,058.5
South Korea (KSE)	122.66	93.968	0.3956	2,967.6
Argentina (Merval)	249.74	160.73	0.5796	4,691.3*

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 7.27. Forecast Error Statistics for the Random Walk Model (Monthly Data)

The random walk volatility forecast is expressed as:

$$h_{t+1} = s_t^2$$

where s_t^2 is the true volatility for period t.

Index	**RMSE**	**MAE**	**MedAPE**	**MedSE**
France (CAC40)	187.46	139.95	0.8653	9,813.1
Germany (DAX)	174.07	140.42	0.9855	10,538
Japan (Nikkei 225)	31.325	23.587*	0.3380*	492.27*
US (DJIA)	56.522	41.236	0.9574	916.94
US (S&P 500	53.984	36.850	0.6184	761.57
US (NASDAQ)	114.23	90.400	0.8683	8,019.7
Hong Kong (Hang Seng)	330.87	190.72	0.8447	5,775.7
Singapore (SST)	474.76	279.43	0.9754	9,721.8
South Korea (KSE)	322.01	260.69	0.8487	37,961
Argentina (Merval)	319.34	282.85	0.9448	70,337

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 7.28. Forecast Error Statistics for the Exponential smoothing Model (Monthly Data)

The exponential smoothing volatility forecast is expressed as:

$$h_{t+1} = \phi_T h_t + (1 - \phi_T) s_t^2$$

where ϕ is the smoothing parameter and s_t^2 is the true volatility.

Index	RMSE	MAE	MedAPE	MedSE
France (CAC40)	80.329	64.487	0.7779	6,643.4
Germany (DAX)	132.93	106.98	1.0583	6,492.8
Japan (Nikkei 225)	49.295	37.569	0.5415	624.60
US (DJIA)	28.163	18.999	0.4758	150.98
US (S&P 500	28.881	21.126	0.3661*	113.97*
US (NASDAQ)	48.382	43.733	0.4810*	2,014.5
Hong Kong (Hang Seng)	109.22	97.680	1.4577	10,627
Singapore (SST)	113.63	98.258	0.7781	9,242.0
South Korea (KSE)	101.47	98.376	0.7164	9,160.9
Argentina (Merval)	155.35	132.68	0.6555	16,690

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. An asterisk indicates that the model gives the best forecast for that forecast error statistic.

Table 7.29. Best Forecast Model for the GARCH type and Stochastic Volatility Models (Monthly Data)

Index	RMSE	MAE	MedAPE	MedSE
France (CAC40)	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Germany (DAX)	SV	GJR	SV	GJR
Japan (Nikkei 225)	GJR	GJR	GJR	GJR
US (DJIA)	ACGARCH	ACGARCH	ACGARCH	ACGARCH
US (S&P 500	SV	SV	SV	SV
US (NASDAQ)	GJR	SV	GJR	SV
Hong Kong (Hang Seng)	SV	SV	GJR	GJR
Singapore (SST)	SV	SV	SV	SV
South Korea (KSE)	GJR	GJR	GJR	GJR
Argentina (Merval)	GJR	GJR	GJR	GJR

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. GJR, ACGARCH and SV denote the GARCH/GJR, CGARCH/ACGARCH and stochastic volatility models respectively.

Table 7.30. Best Forecast Model Overall (Monthly Data)

Index	RMSE	MAE	MedAPE	MedSE
France (CAC40)	ACGARCH	ACGARCH	ACGARCH	ACGARCH
Germany (DAX)	SV	GJR	SV	HM
Japan (Nikkei 225)	GJR	RW	RW	RW
US (DJIA)	ACGARCH	ACGARCH	ACGARCH	ACGARCH
US (S&P 500	SV	SV	ES	ES
US (NASDAQ)	GJR	SV	ES	SV
Hong Kong (Hang Seng)	HM	HM	HM	HM
Singapore (SST)	HM	HM	SV	SV
South Korea (KSE)	GJR	GJR	GJR	GJR
Argentina (Merval)	GJR	GJR	GJR	HM

Notes: RMSE is the root mean squared error statistic defined in (4.5.1); MAE is the mean absolute error statistic defined in (4.5.2); MedAPE is the mean absolute percentage error statistic defined in (4.5.3); MedSE is the median squared error statistic defined in (4.5.4). The forecast period is 8/9/1998 to 22/2/1999 respectively. GJR, ACGARCH, SV, HM, RW and ES denote the GARCH/GJR, CGARCH/ACGARCH, stochastic volatility, historical mean, random walk and exponential smoothing models respectively.