Which Market Enhances Market Efficiency by Improving Liquidity?

Evidence of Market Liquidity in Relation to Returns of Stocks

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Abstract

Market efficiency can be enhanced by market liquidity if it promotes value creation, leading to increasing stock returns. A positive relation between liquidity and stock returns implies capital movement towards more efficient investment at a low cost for value creation. Existing studies are controversial for the relation being positive, negative, or inconclusive. With such inconsistency, this paper employs data from more than 3200 company stocks from the UK, US, German and China securities markets over a 10-year period to estimate the relation across these four markets, respectively. The framework of estimation is robust to outliers and macro shocks, whilst eliminating the issues of multicollinearity, autocorrelation and endogeneity. The study finds some interesting results. We report strong evidence for Germany and the UK of a positive relationship between returns and liquidity. In contrast, China exhibits the opposite result, and the US provides inconclusive evidence, possibly caused by significant diversification of value perception on liquidity. Our results imply that the German and the UK markets are more efficient than the emerging market of China because liquidity assists capital movement more efficiently. The policy implication of this research is that, for emerging stock markets, the costs of capital movement should be reduced in order to increase the efficiency of funding allocation.

Keywords: *Liquidity, Stock returns, Market Efficiency, Amihud Ratio, German Stock Market, UK Stock Market, US Stock Market, China Stock Market*

JEL Classification: ***G1, G15, G140***

1. Introduction

Liquidity assists capital movement at a low cost, which facilitates funds moving to more efficient investments from less efficient ones or to a need in response to market shocks. Liquidity stimulates arbitrage trades to reduce the bid-ask spreads, which enhances market efficiency (Chordia et al. 2008). Stock liquidity creates firm value by moving capital more efficiently to new investments of firms for improvement of corporate control and governance (Cheung et al. 2015), and good governance attracts more investors (Luo 2022). These arguments imply that a positive effect of liquidity on changing stock value and returns is expected, particularly when the improvement of cost efficiency for capital movement is valued by stock markets.

The positive association between stock liquidity and returns has been widely evident in the previous academic literature. On the basis of the firm-level studies, Amihud and Mendelson (1991) and Eleswarapu and Reinganum (1993) report a positive relationship between stock liquidity and the returns for the US market. This finding is further evident by Brennan and Subrahmanyam (1996) using New York Stock Exchange (NYSE) data, Nguyen and Lo (2013) for the New Zealand stock market, Assefa and Mollick (2014) for the African stock market, and Narayan and Zheng (2011) for the Chinese stock market. Huang and Ho (2020) argue that the stock liquidity component of earnings management is positively associated with future stock returns in Chinese firms. Gofran et al. (2022) report that stock liquidity is positively (negatively) related to returns around the announcement of good (bad) news.

However, the opposite evidence is also found by studies using different liquidity measures and firm-level estimation. Amihud and Mendelson (1986) introduce a new liquidity measure to study the relation and find empirical evidence from the US market that higher stock liquidity reduces returns. This negative relation has been further observed by studies using a volume-based approach to measure liquidity, such as Datar et al. (1998), Brennan et al. (1998), Chordia et al. (2001), Lesmond (2005), Keene and Peterson (2007) and Chan and Faff (2005). The consistent result of the negative relationship is also identified by studies either using the price-based liquidity measure, such as Amihud (2002), or using a transaction-cost-based measure, for instance, Sarr and Lybek (2002). Following Amihud (2002) on the illiquidity return premiums, Amihud et al. (2015) report higher premiums with lower liquidity on average across 43 economies over 252 months. Their finding is based on the average of cross-country samples without disclosing the relationship individually or dynamically against different periods. Huang and Ho (2020) report an increase in stock liquidity with a fall in the degree of earnings management for Chinese companies.

The premium for illiquidity implied by the negative relationship (Amihud 2002) is also shown by studies on the Chinese stock market, such as Eun and Huang (2007). Interestingly, Eleswarapu and Reinganum (1993), which utilizes the same method and has a similar dataset to Amihud and Mendelson (1986), discover an opposite result on the relation of liquidity to stock returns. When the two opposite effects of liquidity on the returns are mixed in data, it is not surprising to find either inconsistent or inconclusive results of the study on the relationship that has been reported, for instance, by Rouwenhorst (1999), Marshall and Young (2003), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Wang and Di Iorio (2007), Lee (2011), and Lam and Tam (2011). No evidence on the relationship between market liquidity and stock returns in the Norwegian stock market was found for the period 1983–2015 by Leirvik et al. (2017). Cakici and Zaremba (2021) employ several established liquidity measures in 45 countries for the years 1990–2020 and find liquidity and stock returns depending strongly on firm size.

As we have summarized above, the evidence from existing studies is quite controversially divided on what the liquidity effect is on stock returns. Prior studies find positive, negative or inconclusive evidence. In our research, we argue that the empirical relationship depends on the market perception in valuing liquidity. When the market perceives the value of illiquidity for premiums, then illiquidity drives up stock returns. In this case, we expect to witness a negative pattern of liquidity in relation to stock returns. Otherwise, if the market perceives the value of liquidity as the low cost of capital movement to more efficient investment, or as a response to market shocks, or to facilitate ownership change via acquisition for corporate control and governance improvement Cheung et al. (2015), then liquidity drives up the stock value and returns. In this case, we envisage observing the positive pattern of liquidity in relation to stock returns, reflecting market efficiency.

In view of the above, an empirical pattern of the relationship in a market over time becomes an interesting research question, since it can indicate if the market is efficient for capital movement at a low cost. We attempt to answer this query on the relation of liquidity with stock returns because of the inconclusive evidence provided by previous research and also for the important implication to stock market efficiency. Since Fama and MacBeth (1973), existing studies have provided mixed perceptions or arguments on the question. On the one hand, we can find consistent estimations across different markets, different time periods and different research methods. On the other hand, we can also find inconsistent results not only from using different data, different sample periods, and different research methods, but also even from using similar data. Clearly, more robust evidence is needed to solve the current debate. In this context, our paper will take an internationally comparative approach to study the relationship more robustly from two aspects of comparison: time dynamics and market horizon.

In our study, we collect data from Bloomberg on the four most representative stock markets in the world: the UK as one of the oldest financial markets in the world with securitization of more than 150% of its GDP, the US as the largest and most liquid market in the world with securitization of more than 150% of its GDP, Germany as the largest manufacturing economy in the world that has a low securitization of 60% of the GDP, and China as the largest emerging market in the world.[1] We process the daily trading information of the stocks to monthly-based data and edit it for a robust sample that is less sensitive to the effect of outliers. Our robust sample has monthly-based 436,217 observations at a stock level over the period of 144 months from 2002 to 2013 for estimation. We further divide the sample period into three sub-periods according to the pre-financial crisis (2002-06), during the financial crisis (2007-09) and post-financial crisis (2010-13), which helps perform comparative analysis across time for each market.[2]

One challenge in using market liquidity to estimate its effect on stock returns is how to measure market liquidity. Our study takes two measurements to compare the consistency of estimation. The first is the common factor approach. We apply Asymptotic Principal Component (APC) developed by Korajczyk and Sadka (2008) to extract factors embedded commonly across both liquidity measures and stocks. The factors derived from the extraction capture information related to the co-variation of liquidity across stocks and measures, which is called the "commonality of liquidity" of a market Chordia et al. (2000). The commonality of liquidity has been identified by a number of studies in an attempt to measure market liquidity (Huberman and Halka 2001; Fabre and Frino 2004; Brockman et al. 2009). Mancini et al. (2013) regard the common factor of liquidity as the proxy of market liquidity. In line with these studies,

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[1] Stock prices co-movement can be explained by the existence of global common shocks and portfolio adjustments by international investors (Hirayama and Tsutsui 2013). However, insider trading is detrimental to the resource allocation mechanism of the market (Dissanaike and Lim 2015).

[2] The credit crunch financial turmoil of 2007 may have changed the dynamics of stock markets (McKibbin and Stoeckel 2010; de Menil 2010)

we derive an across-measure-and-stocks common factor of liquidity as a proxy of market liquidity for exploring its relationship with stock returns in different markets and time periods.

In the second approach, we average the liquidity of all stocks, excluding the concerning stock, as a measure of market liquidity of the concerning stock. This is called the rival average of the market for the concerning stock, which is widely used in the study of industrial organization in measuring the average output of rival firms Hay and Liu (1998). We apply this idea to measure market liquidity as it has a clear exogenous relationship with the returns of the concerning stock, because the stock is dropped out from the calculation of the average liquidity of the market. Clearly, the second approach provides an advantage in estimating the liquidity-returns relationship exogenously. It also enables us to use panel data as a robustness examination to compare estimation from the commonality approach.

In estimation of the relationship between liquidity and returns, one common issue is the misspecification of the models in estimation by omitting the control of macroeconomic conditions and policy shocks. Without the control, estimation can pick up the mixed effects of liquidity and macroeconomic shocks on the returns, which results in a biased estimation of the relationship. This problem is particularly acute in estimating the effect of the market liquidity on the stock-level returns, because, at the market level, both the liquidity and macroeconomic elements are easily distressed. Apergis et al. (2015) find evidence on the relationship of liquidity to macroeconomic conditions for both the UK and Germany. As a result, we introduce time dummies to control for the impact of the macroeconomic shocks in estimation and employ the first difference of the market liquidity to mitigate the multicollinearity problem brought by the introduction of time dummies in estimation.

With the control of macro shocks and the multicollinearity in estimation, our research makes further augments of estimation from existing studies by refining the classic Amihud momentum for estimation, because we identified a flaw of the classic momentum that has an accounting link with the present stock returns. Moreover, we also consider a possible presence of the autocorrelation of the refined momentum with the present stock returns by introducing the instrumental momentum in estimation. These augments provide our paper with a methodological advantage in estimating a robust relationship between liquidity and stock returns.

After we apply our robust estimations of the relationship between liquidity and stock returns, which distinguishes us from prior research, we identify strong and dynamic evidence for Germany and the UK that both have a positive pattern of liquidity in relation to the returns consistently across three time periods. In contrast, the Chinese market has the opposite result, which has a very dominantly negative pattern across the three time periods. Interestingly, as the largest stock market in the world, the US has inconclusive evidence for the empirical association between liquidity and stock returns. This may be caused by the significant diversification of the value perception on liquidity. When liquidity enhances market efficiency Chordia et al. (2008), our findings are profound in terms of its implication. The UK and Germany are more conducive for market efficiency from the perspective of the low cost of capital movement. In contrast, China is not, and the US is mixed or inconclusive. Our results imply that markets are different. Some markets value liquidity and are more efficient, while others value illiquidity and are less efficient. This view is particularly distinctive from Amihud et al. (2015), which state that markets across countries as homogenous in valuing illiquidity for higher return premiums. If the view of Amihud et al. (2015) holds, then it implies all stock markets over the world would behave in the same manner in terms of enhancement of market efficiency. This appears like a very unrealistic point of view.

The rest of this paper is organized in the following way. In the next Section, we outline the research methods used in our research, Section 3 reviews the data and descriptive statistics, Section 4 discusses the empirical estimation and results, and Section 5 concludes.

2. Model specification and measurements of market liquidity

2.1 Specification of estimation models

Following Amihud (2002), a time-series model is utilized to investigate the impact of market liquidity on stock returns,

$$R_t - R_t^f = a_0 + \theta L_{t-1} + \rho L_t^{UN} + bX_{t-1} + \varepsilon_t \quad (1)$$

where t represents monthly intervals, R_t is the market average stock returns of listed firms and R_t^f is the risk-free rate. L_{t-1} and L_t^{UN} are the lagged and unexpected stock market liquidity, respectively. X_{t-1} is a vector of other controlling variables that affect stock returns. The impact of market liquidity on stock returns is measured by the coefficient θ.

Equation (1) can be extended to the Amihud Commonality-Factor Model in which the market liquidity is defined as the lagged across-measure-and-stock liquidity common factor (L_{t-1}^C), extracted by the Asymptotic Principal Components (APC) method (Korajczyk and Sadka 2008),

$$R_t - R_t^f = a_0 + \theta L_{t-1}^C + bX_{t-1} + \varepsilon_t \quad (2)$$

Furthermore, Eq. (2) can be used as a panel-data estimation model (i.e., Amihud Commonality-Factor Panel Estimation Model) to investigate the market liquidity effect on firm-level stock returns, by estimating the model below,

$$R_{i,t} = a_0 + \theta L_{t-1}^C + bX_{i,t-1} + F_i + \varepsilon_{i,t} \quad (3)$$

where $R_{i,t}$ is the returns of stock i, and $X_{i,t-1}$ is a vector of one-month lagged firm characteristic variables that control other effects on stock returns. F_i and $\varepsilon_{i,t}$ are firm dummies and the error term, respectively.

To test the robustness of the Amihud Commonality-Factor Panel Estimation Model of Eq. (3), we introduce a new approach to measure market liquidity as

$$\overline{L}_{j,t}^{M} = \left(\frac{\sum_{j=1}^{N} L_{j,t} - L_{i,t}^{M}}{N-1} \right) \quad j \neq i \tag{4}$$

where $L_{j,t}$ is the liquidity of individual stock j, $L_{i,t}^{M}$ is the liquidity of the concerning stock i, $\overline{L}_{j,t}^{M}$ is the average liquidity of all stocks on the market by excluding the concerning stock i, and N is the number of stocks. M implies a measure applied to compute the liquidty of a stock. Since stock i is excluded from the computation, this average is referred to as ***the rival average of liquidity*** for stock i. This concept is acquired from the average output of rival firms widely used by the study of industrial organization (Hay and Liu 1998) to compute the outputs of all rival firms for firm i. We replace L_{t-1}^{C} with $\overline{L}_{j,t}^{M}$ in Eq. (3) to obtain the model as

$$R_{i,t} = a_0 + \lambda \overline{L}_{j,t}^{M} + bX_{i,t-1} + F_i + \varepsilon_{i,t} \tag{5}$$

The rival average of liquidity $\overline{L}_{j,t}^{M}$ brings two advantages in the estimation of Eq. (5). First, it enables full panel estimation of the market liquidity effect on the returns using a large sample, which will be more informatively robust. Second, we treat $\overline{L}_{j,t}^{M}$ as exogenous in relation to the estimation of the returns $R_{i,t}$ since $\overline{L}_{j,t}^{M}$ excludes information of stock i. In previous studies, the endogeneity issue has been identified when examining the average liquidity of all stocks to concerning stock's returns (see among others, Amihud and Mendelson (1986), Amihud (2002), and Hameed et al. (2010)). We suggest that the rival average helps avoid the endogenous problem in the estimation without compromising its representativeness to the market average when the sample is large.

Furthermore, in estimating the market liquidity effect on the returns, one problem is that the market liquidity can often be disturbed by macroeconomic shocks, causing a model misspecification problem that results in biased estimation if the control of shocks is omitted. In order to separate the liquidity effect from macroeconomic shocks, a time dummy is introduced in the estimation of Eq. (3) and Eq. (5),

$$R_{i,t} = a_0 + \theta L^C_{t-1} + bX_{i,t-1} + F_i + D_T + \varepsilon_{i,t} \tag{6.1}$$

$$R_{i,t} = a_0 + \lambda \overline{L}^M_{j,t-1} + bX_{i,t-1} + F_i + D_T + \varepsilon_{i,t} \tag{6.2}$$

where D_T is a time dummy to control the effect of macroeconomic shocks that usually last over a year. To mitigate the effect of multicollinearity between the year dummy and the market liquidity in the estimation of Eq. (6.1) and Eq. (6.2), we replace level-based variables, L^C_{t-1} and $\overline{L}^M_{j,t-1}$, with their first differences, ΔL^C_{t-1} and $\Delta \overline{L}^M_{j,t-1}$, respectively,

$$R_{i,t} = a_0 + \theta \Delta L^C_{t-1} + bX_{i,t-1} + F_i + D_T + \varepsilon_{i,t} \tag{7.1}$$

$$R_{i,t} = a_0 + \lambda \Delta \overline{L}^M_{j,t-1} + bX_{i,t-1} + F_i + D_T + \varepsilon_{i,t} \tag{7.2}$$

Having controlled both stock/firm specific effects and macro shocks, the estimation of Eq. (6.1), (6.2) and (7.1) and (7.2) for θ and λ that captures the effect of the liquidity on the stock returns. We also estimate Eq. (3) and Eq. (5) for a direct comparison of results between those without control of macro shocks, those with control of the macro shocks, and those with mitigation of the multicollinearity of time dummy to the market liquidity variable. We expect θ and λ shall be consistent if the estimated results are robust. These models will be estimated respectively over three time periods of the sample: the pre-crisis period (2002-06), the during-crisis period (2007-09), and the post-crisis period (2010-13). In addition, the January effects emphasized by both Eleswarapu and Reinganum (1993) and Amihud (2002) are also considered in our empirical estimation.

2.2 Specification of market liquidity in the estimation

In the estimation of the liquidity-returns models discussed above, market liquidity is the key variable. This section discusses the two measurements used in our analysis, i.e., the commonality factor of liquidity (L^C_t) and the rival average of liquidity ($\overline{L}^M_{j,t}$).

2.2.1 Measuring the common factor of liquidity

First, with a large sample, we follow Korajczyk and Sadka (2008)'s Asymptotic Principal Components (APC) Method to compute ***the common factor of liquidity*** across both measures and stocks as a proxy of market liquidity for each economy at month t. We extract the liquidity common factor $L^c = [L_1^C, L_2^C, \dots L_{t-1}^C, L_t^C]'$ for each month of a market by solving

$$(\eta^* I - \Omega^q)L^c = 0 \tag{8}$$

where I is an $K \cdot K$ identity matrix, and K has 144 months from January 2002 to December 2013. η^* is the largest eigenvalue of η solved from

$$|\eta I - \Omega^q| = 0 \tag{9}$$

where the matrix Ω^q is specified as

$$\Omega^q = \frac{IL^{q\prime} IL^q}{M'M} \tag{10}$$

where $IL^{q\prime}$ and M' are a transpose of the matrix IL^q and M, respectively. M is $N \cdot K$ matrix that can assist with the issue of missing data. N contains all stocks for a market. IL^q as a matrix that stacks up three illiquidity measures: the Quoted Proportional Spread, the Amihud illiquidity Ratio, the reversed Turnover Ratio of liquidity.[3]

2.2.2 Measuring the rival average of liquidity

As an alternative measure of market liquidity, we introduce the rival average of liquidity. The new measure has been discussed with respect to its calculation and econometric properties in Eq. (4) and Eq. (5). Here, our discussion focuses on which measure we shall select from the three liquidity measures for computing the average. The rule of our selection is to rank the correlation of each stock liquidity measure with the commonality factor ($L_{i,t}^C$) derived

[3] The specifications of these measurements and the matrix see Appendix A.1.

from the common co-variation of the three measures, and then select the one with the highest rank: $Corr(IL_{i,t}^{S}, L_{i,t}^{C})$, $\mathrm{Corr}(IL_{i,t}^{A}, L_{i,t}^{C})$ and $Corr(IL_{i,t}^{T}, L_{i,t}^{C})$. This is because the highest correlation implies that the measure is the best representable for the commonality factor, and therefore suggest strong consistency in using either of the two market liquidity measures to estimate the relationship between liquidity and returns.

Table 1 shows the Quoted Proportional Spread of illiquidity (IL_{it}^{S}) that has the highest rank of the correlation. We also plot both $IL_{i,t}^{S}$ and $L_{i,t}^{C}$ for their movement against time in Fig. 1. The movement of the market illiquidity versus the market liquidity is highly mirrored with each other, indicating the consistency between the two measurements of market liquidity. Therefore, we select ***the quoted spread of illiquidity*** to compute the rival average of illiquidity in Eq. (4) for estimation.

[Table 1 and Figure 1]

2.3 Specification of other variables in the estimation

2.3.1 Monthly stock returns

To estimate Eq. (3), (5), (6.1), (6.2), (7.1) and (7.2), the dependent variable of monthly stock returns is defined as

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{11}$$

where $R_{i,t}$ is monthly investment returns of stock i in month t, $P_{i,t}$ is the last stock price of firm i on the last day of month t, and $P_{i,t-1}$ is the last price on the first day of month t.

2.3.2 The volatility variable for risk control

In the literature the volatility of stock returns is regarded as one of the risk factors, and empirical evidence reports that there is a significant association between stock price volatility and stock returns. Therefore, we include the volatility of stock returns denoted by $V_{i,t}$ as one of the control variables for the estimation of our models. This variable is defined as the monthly standard deviation of daily stock returns of stock i in month $t-1$, which is calculated as

$$V_{i,t} = \sqrt{\frac{1}{N}\left[\left(R_{i,\tau} - \bar{R}_{i,t}\right)^2 + \left(R_{i,\tau+1} - \bar{R}_{i,t}\right)^2 + \cdots + \left(R_{i,\tau+N-1} - \bar{R}_{i,t}\right)^2\right]} \qquad (12)$$

where N is the number of trading days of stock i in month t, $R_{i,\tau}$ is the stock return of firm i at the first trading day τ in month t, and $\bar{R}_{i,t}$ is the monthly average daily stock returns of firm i in month t. We use the volatility to control the risk effect in the estimation, instead of using 'beta' that has been controversial and dropped from estimation by some studies, such as (Chordia et al. 2009). This is because it exhibits measurement error (Datar et al. 1998; Bodie 2003; Elton et al. 2014), it presents the size portfolios that is highly correlated with the size of the firm (Amihud 2002), and it is inconsistent. Finally, a non-robust relationship with the returns is found by Fama and French (1992) and Eun and Huang (2007).

2.3.3 Firm size

Amihud (2002) regards firm size (the market capitalization of the firm) as one of the liquidity-related variables. Datar et al. (1998) also take the firm size as a control variable in the estimation of the returns and liquidity relationship. Fama and French (1992) suggest that the effects of trading volume on the expected excess returns of stocks decline from small to large companies. In line with these arguments, we control the effect of the firm size in the estimation, and we measure the firm size as the natural logarithm of the market capitalization of firm i at the end of month t, denoted by $LnS_{i,t}$.

Since our sample consists of mostly industrial firms, the ratio of the book value to the market value (size) is not included in our estimation. This is because our sample includes banks and financial firms that usually have a comparatively high leverage ratio which makes the book-to-market ratio insignificant (Fama and French 1992).

2.3.4 The control variable for the momentum effects

After the introduction of the momentum aspect to capture the effect of past stock returns on the current returns by Carhart (1997), two momentum factors were considered by Amihud (2002) for the estimation of the returns-liquidity relationship.

Following Amihud (2002), $R^{100}_{i,t-1}$ is defined as the *first* momentum factor to capture the effect of the nearer past returns on the current returns for stock i. According to Amihud (2002), the past returns are specified as the returns over the investment window from the last day of the month $t-1$ counted back to the 99th day or the 100th day back from the first trading day of the month t.

However, Amihud's $R^{100}_{i,t-1}$ has a flaw in the estimation since it generates an accounting link between $R_{i,t}$ and $R^{100}_{i,t-1}$. The link implies that $R^{100}_{i,t-1}$ can no longer be 'pre-determined' exogenously, creating an endogeneity problem of the first momentum in the estimation. To address the issue, we amend the computation of $R_{i,t}$ from using the price on the last trading date of the present month less one on the last trading date of the previous month, to using the price on the last trading date of the present month less one on the first date of the present month. Our amendment indirectly refine Amihud's $R^{100}_{i,t-1}$ in order to avoid the accounting link between $R_{i,t}$ and $R^{100}_{i,t-1}$.[4]

Furthermore, if the stock price on the first date of month t and the price on the last date of month $t-1$ are auto-correlated, this may cause a dynamic relation of the refined $R^{100}_{i,t-1}$ to

[4] An example of the first momentum factor is illustrated in Appendix A.2., together with explanations on the accounting link.

$R_{i,t}$, although the two variables are not same in terms of their structure. These possible dynamics could create an endogenous issue for the refined $R_{i,t-1}^{100}$ if the first-order autocorrelation of the disturbance term appears in the estimation. To take this argument into account, we instrument the refined $R_{i,t-1}^{100}$ using $R_{i,t-2}^{100}$ with an underlying assumption that the second-order autocorrelation of the disturbance term is null in the estimation. We estimate θ and λ by using the instrumental variable of the refined $R_{i,t-1}^{100}$ for Eq. (7.1) and (7.2) as our further robust test to the consistency of our estimations.

The *second* momentum factor is also considered by Amihud (2002) to capture the effect of the further past stock returns on the present returns. In order to apply this to our research, we define the variable of the second momentum as the past returns over an investment window [-365, -101] with the first trading day of the month as 0.[5] The second momentum factor $R_{i,t-3}^{265}$ is considered as a strict exogenous variable in the estimation as it fails to reject the null hypothesis for the third-order autocorrelation of the disturbance term.

To summarize the above, the other control variables introduced for our estimation of Eq. (6.1), (6.2), (7.1) and (7.2) are

$$bX_{i,t-1} = b_1 \cdot V_{i,t-1} + b_2 \cdot LnS_{i,t-1} + b_3 \cdot R_{i,t-1}^{100} + b_4 \cdot R_{i,t-3}^{265} \tag{13}$$

3. Data sample and descriptive statistics

All company stocks listed either in NYSE, German Stock Exchange, London Stock Exchange, or China including both Shanghai and Shenzhen Stock Exchange are collected from Bloomberg over the period from 1 December 2001 to 31 December 2013. We acquire daily information on the five variables below: (i) Last Price: the daily closing price;[6] (ii) Bid Price

[5] An example of the second momentum factor is illustrated in Appendix A.2.

[6] Daily prices of stocks are in a currency of US dollars for the US listed firms at a range from $1 to

and Ask Price: the last daily bid price and ask price respectively; (iii) Trading Volume: the number of total shares being traded in one day; (iv) Shares Outstanding: the number of shares outstanding; (v) Market Capitalization: the total value of a firm in the financial market calculated as the last price of the stock multiplied by the total number of its shares outstanding.

We select our sample of company stocks according to the following two criteria. First, we require two consecutive years of trading as a minimum during 2000 to 2013, and 200 or more days traded over a year as primary on either of the four markets. Second, in line with Chordia et al. (2000) and Korajczyk and Sadka (2008), firms categorized as Funds, ADRs, Units and REITs are excluded from our sample selection.

With the total sample selected above, which contains the daily information on the five variables for each stock, we compute monthly liquidity at a stock level and at a market level respectively, as well as other variables discussed above. Following existing studies such as Amihud (2002), Korajczyk and Sadka (2008) and Chordia et al. (2009), we further refine our sample by excluding the missing observations and outliers of either market size or a liquidity measure at the highest or the lowest 1% of the data sample of each market. We also exclude observations with monthly returns greater than 100% or lower than -100% over a month.[7]

In the robust sample, we have 440 German company stocks, 425 UK stocks, 1194 US stocks and 1093 Chinese stocks from 2002 to 2013. There are 436,217 observations in total for four markets over 144 months. We plot the average stock price and the returns of each country over 144 months in Figure 2 and Figure 3, respectively. The Figures show that each of the four

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$900, Euro for Germany at range from Euro1 to Euro 999, GB pound for the UK at a range from £1 to £999, and RMB for China from 1 yuan to 100 yuan, which is collected in line with the study of Korajczyk and Sadka (2008).

[7] A visual check of outliers is explained in Appendix A.3.

markets experienced a dramatic price fall (more than 50%) during the period of financial crisis especially in 2007 and 2008. The similar pattern has also been shown when it comes to the average stock returns during the financial crisis period. Moreover, the volatility of the stock returns in the Chinese stock market, the only emerging market in our sample, is higher than the other three mature stock markets particularly in the period of financial crisis although the Chinese government sets the limit to both directions of daily stock prices.

[Figure 2 and Figure 3]

The mean, median and standard deviation of variables including the stock returns ($R_{i,t}$), the rival average of market illiquidity ($\overline{L}^{M}_{j,t-1}$), the volatility ($V_{i,t-1}$), the firm size ($LnS_{i,t-1}$), the refinement of the first momentum ($R^{100}_{i,t-1}$) and, the second momentum ($R^{265}_{i,t-3}$) are reported for each market in Table 2. As expected, the majority of variables are right-skewed, which is consistent with previous studies. Based on the market illiquidity using the cost-based measure of the Quoted Proportional Spread for 2002-2013, overall the Chinese market was the most liquid out of the four markets while the German market was the most illiquid. For the firm size, the average size is 1.43 billion Euro for Germany, £1.89 billion for the UK, $5.20 billion for the US and 4.64 billion RMB for China, respectively.

[Table 2]

4. Estimation and discussion

We split our data sample into three time periods, pre-financial crisis, during-crisis and post-crisis, for each of the four nations. We use two opposite measures of liquidity, the common factor of market liquidity and the rival average of market illiquidity, to evaluate the robustness and consistency of our results. We have five stages of investigation. First, it starts by estimating Eq. (3) and (5) which have been widely applied in prior research to examine the association between returns and liquidity.

These two models are mis-specified since they fail to control the impact of macroeconomic shocks on stock returns. The importance of controlling macro shocks has been evident clearly by our reported Likelihood Ratio statistic (LR-$\chi 2$), which overwhelmingly rejects the hypothesis that shocks do not have an impact on the returns. Furthermore, without the control of shocks we witness that the estimation of the relationship between returns and liquidity is inconsistent across time periods and samples. To address this issue, we estimate Eq. (6.1) and (6.2) as the second stage in order to encapsulate the impact of macroeconomic shocks on the association between liquidity and returns.

Third, due to the interaction of the market liquidity with macroeconomic shocks, it could create serious multicollinearity between year dummies that capture the shocks and the variable of market liquidity in estimation.[8] Therefore, we employ the first difference of the liquidity variable for estimation, as indicated by Eq. (7.1) and (7.2).

Fourth, as argued by both Eleswarapu and Reinganum (1993) and Amihud (2002), the January effect needs to be controlled or removed from empirical estimation because the behavior of market investment is less regular in that month. To take this into account, we estimate the relationship by excluding January to see if our estimated results could be more robust after dropping less-normally-behaved observations.

The final stage is to examine the consistency and robustness of our estimation in the presence of the autocorrelation of the first momentum $R_{i,t-1}^{100}$ to the returns $R_{i,t}$, which may be

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[8] We use Germany as an example to show the correlation between year dummy variables and the liquidity variables. Some dummies exhibit a correlation with liquidity as high as 75%, such as $Corr\left(\bar{L}_{jt-1}^{M}, \mathrm{YR07}\right) = 0.711$. In contrast, the first difference of the liquidity variables reduces correlation dramatically, such as $Corr\left([\Delta\bar{L}_{jt-1}^{M}, \mathrm{YR07}\right) = 0.03$. This indicates the legitimacy of applying Eq. (7.1) and (7.2), that employ the first difference of the liquidity variable for estimation.

caused by the autocorrelation of the first-date price of the month t to the last-date price of the month $t-1$. We replace the refined $R^{100}_{i,t-1}$ by its instrumental variable predicted by $R^{100}_{i,t-2}$ for estimating Eq. (7.1) and (7.2), in order to see if our estimated results from stages three and four can be consistent. The Hausman statistic is employed to test the presence of the dynamic effect on our estimations. The instrumental $R^{100}_{i,t-1}$ is applied in the estimation when the significance of Hausman statistic is reported. We find hardly any significant evidence of the presence of the autocorrelation effect for the case of Germany and the UK, but quite clear evidence for the US and China.

All estimations are carried out by the Least Square Dummy Variables (LSDV) panel data estimation technique, controlling both the firm/stock specific effects captured by firm dummies and the macroeconomic shocks captured by year dummies. We summarize findings with a focus on reporting the estimated results of the returns-liquidity relation, λ and θ, in Table 3.[9]

[Table 3]

The summary report displayed in Table 3 allows us to directly compare our estimated empirical relationships across different periods and methods for each market. λ is the marginal return effect of illiquidity and θ represents the marginal return effect of liquidity. These two estimated coefficients are expected to be significantly opposite to their signs if estimates are consistent and robust. On this basis, we set up the following rule to rank our findings. First, there is strong evidence of the finding if both the estimated λ and θ have an opposite and significant sign in affecting the returns for the same time period of a market. Second, there is weak evidence of the finding if one of the estimated λ and θ is significant in the same time

[9] The full results of Eq. (7.1) and (7.2) are provided in Appendix A.4, covering four countries across the three time periods. Also, the full results of other models are available upon request to the authors.

period. Third, there is a non-conclusive finding if both the estimated λ and θ are insignificant, or both λ and θ are contradictory in having the same significant sign, for the same time period. We apply these three ranking rules to evaluate our findings of the relationship between liquidity and stock returns for each market in turn below.

4.1 Germany

The estimated θ and λ in the first row of the Germany Panel of Table 3 are based on model (3) and (5) without controlling for macroeconomic shocks. The results are not persistently consistent across three time periods. The θ and λ in the second row of Table 3 are based on model (6.1) and (6.2), which suffers the serious effect of multicollinearity between the year dummies and the level variable of market liquidity. The multicollinearity can cause inefficient estimation that may mislead estimated signs and significance of coefficients. The estimated θ and λ in the third row are based on model (7.1) and (7.2) that has taken the first difference of liquidity to mitigate the multicollinearity effect. Interestingly, the sign of θ and λ in the third row is the opposite to the signs shown in the second row, demonstrating the serious effect of multicollinearity in the estimation. For robustness, the estimated θ and λ in the fourth row are estimated by dropping the January effect, which are consistent with the estimates in the third row. Furthermore, in the fifth row, we use instrumental $R_{i,t-1}^{100}$ to replace $R_{i,t-1}^{100}$ to control for the possible effect of endogeneity in the estimation, and the results are very consistent with the estimations in the third and fourth rows. Clearly, on the basis of our ranking rules, the comparative estimates of θ and λ show that it has strong evidence for Germany in the pre-crisis and during-crisis period that liquidity positively affects the returns, and has weak evidence to support this pattern for the post-crisis period. As a result, overall we claim that Germany has a persistently consistent pattern of improvement in market liquidity valued positively for stock investment which raises the returns over time.

4.2 The UK

Similarly, the estimated λ and θ in the first and second row of the UK Panel of Table 3 are not persistently consistent across the three time periods. This could be due to the possible effect from either mis-specification of the model or multicollinearity in estimation. From the third row onwards, we witness a clear pattern of the estimated relationship that consistently appears. A positive effect of liquidity on the returns for the pre-crisis with support of strong evidence is shown in the fourth and fifth rows of estimated λ and θ in the Table. During the financial crisis there is strong evidence shown in the fifth row, as well as for the post-crisis with weak evidence shown in the fourth and fifth rows. On the basis of this evidence, we claim that the UK has a similar pattern to Germany, a persistently consistent pattern of improvement of market liquidity valued positively for stock investment over time.

4.3 The US

In the third, fourth and fifth rows of the US Panel of Table 3, we find that both the estimated λ and θ are significantly opposite to each other, providing strong evidence on the negative effect of liquidity on the returns for the pre-crisis period. The negative relation implies the market is dominated by overall perception that demands premiums for illiquidity (Amihud 2002). This finding has not been extended to the during-crisis and the post-crisis period, since estimated λ and θ in the same rows show inconclusive findings for these two periods.

We further check the inconclusive finding by examining a group of outliers lying far away from the most scattered range of the sample.[10] We find that, in the outlier group, which represents around 9% of the total sample observations, it has a significant coefficient of -0.018 for λ and a significant value 0.188 for θ in the during-crisis period. We also witness a

[10] The group of outliers in the US market is discussed in Appendix A.3.

significant value of -0.020 for λ and a significant figure of 2.472 for θ in the post-crisis period, which is strong evidence in support of the positive effect of liquidity on the returns. We also estimate the total sample including the outlier group, and the inconclusive finding remains.

The difference in the findings between the robust sample and the outlier group suggests that the US is quite diversified without a dominant perception for valuing market liquidity. This diversification is also reported by prior research that found different patterns of the returns and liquidity relation for the US market. Some claim positive associations (Eleswarapu and Reinganum 1993; Brennan and Subrahmanyam 1996), several declare a negative relation (Amihud and Mendelson 1986; Datar et al. 1998), and selected studies report ambiguously or inconclusively. Clearly, the evidence here concludes that the US market is inconclusive in terms of the liquidity effect on the returns, because the value perception on liquidity for investment is not dominated by a particular bias over time.

4.4. China

As the largest emerging market in the world, how does China perceive market liquidity for stock investment? Interestingly, the Chinese market values market illiquidity for higher investment premiums persistently over time. The finding on the negative relation is supported by strong evidence present in all three time periods. This can be witnessed in the estimated positive λ and negative θ in the third, fourth and fifth rows of the China Panel of Table 3. The negative relationship between liquidity and returns can also be found in other studies of China's stock market, such as Eun and Huang (2007).

It is noticeable from the first row in the China Panel of Table 3, that without the control of the macroeconomic shocks, our estimation shows a positive relationship for the pre-crisis and the during-crisis period. This finding is also reported by Narayan and Zheng (2011) in their pre-crisis estimation on the Chinese stock market. Evidently, once the misspecification issue is addressed, the estimation becomes negative for three periods robustly, persistently and dominantly. Our results demonstrate that the model misspecification can lead to incorrect empirical estimations.

5. Conclusion

In this paper we attempt to answer the empirical question of how does market liquidity affect the returns of stock investment? If the market perceives the value of illiquidity for premiums, then illiquidity drives up stock prices and returns. In this case, we can observe the negative pattern of liquidity in relation to the returns. Otherwise, if the market perceives the value of liquidity for the low cost of capital movement to more efficient investment or to a need in efficient response to information shocks, then liquidity drives up stock returns. In this case, we can observe the positive pattern of liquidity in relation to the returns. Prior research argues positive, negative and inconclusive associations between liquidity and stock returns. In order to find an internationally comparative view with time dynamics on the relationship between stock returns and liquidity, we choose the four most representative stock markets in the world, Germany, the UK, the US and China, for our investigation across three time periods: the pre-financial crisis (2002-06), during the financial crisis (2007-09) and post-financial crisis (2010-13).

Our empirical analysis begins with the computation of both market liquidity using the widely applied method of common factor to extract the commonality of different measures of liquidity at a stock level, and market illiquidity using the rival average of the cost-spread-based illiquidity measure that is found to be most correlated to the common factor. Using these two opposite measures of liquidity, we expect that the robust finding on the basis of the two measures shall be significantly opposite to each other in terms of their estimated sign. This provides us with a mirror comparison to evaluate our findings according to the strong, weak or inconclusive evidence for the relationship between liquidity and returns over time.

With this research strategy, we make some further augments from previous studies of the empirical relation of liquidity to the returns. First, our estimation is based on a robust sample that makes estimation less sensitive to the effect of outliers. Second, we control the macro shocks in estimation, and the shocks are significantly identified in our estimation. Third, we take the first difference of the liquidity variable that helps mitigate the multicollinearity effect on estimation, making estimation more efficient and robust. Fourth, we remove the January effect because the behavior of market investment is less regular in that month. Finally, we consider the possible presence of the autocorrelation of the first momentum factor with stock returns by using the instrumental values for estimation. These five augments provide the study with a methodological advantage for a more robust estimation of the relation, because a method applied for estimation does matter for finding robust evidence, as shown by our study.

We take the rigorous approach discussed above to process a monthly-and-stock-based large panel sample data of nearly half a million observations across four markets over three time periods of 144 months from 2002 to 2013. We identified strong evidence in the German and UK market that exhibit a positive pattern of liquidity in relation to the returns consistently across three time periods. In contrast, the Chinese market has the opposite effect, given that we discover a dominant negative pattern across the three time periods. Interestingly, as the largest stock market in the world, the US has inconclusive evidence regarding the association between market liquidity and stock returns. A possible cause of this result could be the significant diversification of value perception on liquidity.

The implications of our empirical outcomes are profound. From the aspect of market efficiency, our findings imply that the German and UK markets are more efficient than the emerging market of China, because market liquidity assists capital movement at a low cost.

For the former, liquidity creates value, leading to greater returns, by allowing capital to move cheaply from less efficient to more efficient investment. In contrast for the latter, illiquidity creates value and so returns by adding premiums or costs for capital movement. Therefore, our results suggest that the costs of capital movement should be reduced in order to increase the efficiency of funding allocation for the emerging stock market. Possible ways of cost reduction include improving the transparency of information, lowering costs of transactions, such as stamp duty charged on selling or buying a stock, and imposing stricter regulation on market manipulation.

Appendix

A.1 The three measures of individual stock illiquidity and the matrix

Among previous studies, the illiquidity of individual stock can be measured by three major approaches: the transaction-cost-based measure, the volume-based measure, and price-based measure.

For the transaction-cost-based measure, following Amihud and Mendelson (1986) and Eleswarapu and Reinganum (1993), we define the monthly average of *the Quoted Proportional Spread* to measure stock i's illiquidity in month t, $IL_{i,t}^{S}$, as

$$IL_{i,t}^{S} = \frac{1}{N}\sum_{\tau=1}^{N}\frac{2\left(P_{i,\tau}^{A} - P_{i,\tau}^{B}\right)}{P_{i,\tau}^{A} + P_{i,\tau}^{B}} \quad with\ \ 0 < IL_{i,\tau}^{S} < 1 \qquad (A.1)$$

where $P_{i,\tau}^{A}$ and $P_{i,\tau}^{B}$ are the last ask price and bid price of stock i on day τ respectively. *N* is the number of trading days in month t. A higher Quoted Proportional Spread represents a lower liquidity.

For the price-based measure, following Amihud (2002), we define the monthly average *Amihud Illiquidity Ratio* to measure stock i's illiquidity in month t, $IL_{i,t}^{A}$, as

$$IL_{i,t}^{A} = \frac{1}{N}\sum_{\tau=1}^{N}\frac{\left|R_{i,\tau}\right|}{VOLD_{i,\tau}} \quad with\ 0 \leq IL_{i,\tau}^{A} < 1 \qquad (A.2)$$

where $\left|R_{i,\tau}\right|$ is the daily absolute returns of stock *i* at day τ which is calculated as $\left|R_{i,\tau}\right| = \left|\frac{P_{i,\tau}-P_{i,\tau-1}}{P_{i,\tau-1}}\right|$, where $P_{i,\tau}$ and $P_{i,\tau-1}$ are the last prices of stock i on day τ and day $\tau - 1$ respectively. *N* is the number of trading days in month t. $VOLD_{i,\tau}$ is the daily trading volume of firm *i* on day τ, calculated as $VOLD_{i,\tau} = \sum_{q=1}^{k} P_{i,z} \cdot Q_{i,z}$, where $P_{i,z}$ is the trading price of q^{th} transaction during day τ and $Q_{i,z}$ is the corresponding trading volume. *k* is the number of total transactions during day τ. A higher value of the Amihud Illiquidity Ratio represents a lower liquidity.

For the volume-base measure, following Rouwenhorst (1999), Jones (2002), Chan and Faff (2005), and Koch (2010), we define the monthly average Turnover Ratio to measure stock i's illiquidity in month t, $L_{i,t}^{T}$, as

$$L_{i,t}^{T} = \frac{1}{N}\sum_{\tau=1}^{N}\frac{Q_{i,\tau}}{S_{i,\tau}} \qquad with\ 0 \le L_{i,\tau}^{T} \le 1 \qquad (A.3)$$

where $Q_{i,\tau}$ and $S_{i,\tau}$ are the volume traded and the number of shares outstanding of stock i on day τ respectively. N is the number of trading days in month t. A higher Turnover Ratio represents a higher liquidity. Therefore, to compare all three measurements directly, we reverse the Turnover Ratio as

$$IL_{i,t}^{T} = 1 - L_{i,t}^{T} \qquad (A.4)$$

in which a higher reversed Turnover Ratio represents a lower liquidity.

Next, a matrix IL^{q} is defined to stacks up three liquidity measures as

$$IL^{q} = \begin{bmatrix} \widetilde{IL_{i,1}^{S}} & \dots & \widetilde{IL_{i,t}^{S}} \\ \vdots & \ddots & \vdots \\ \widetilde{IL_{n,1}^{S}} & \dots & \widetilde{IL_{n,t}^{S}} \\ \widetilde{IL_{i,1}^{A}} & \dots & \widetilde{IL_{i,t}^{A}} \\ \vdots & \ddots & \vdots \\ \widetilde{IL_{n,1}^{A}} & \dots & \widetilde{IL_{n,t}^{A}} \\ \widetilde{IL_{i,1}^{T}} & \dots & \widetilde{IL_{i,t}^{T}} \\ \vdots & \ddots & \vdots \\ \widetilde{IL_{n,1}^{T}} & \dots & \widetilde{IL_{n,t}^{T}} \end{bmatrix} \qquad (A.5)$$

where, $\widetilde{IL_{i,t}^{S}} = \frac{IL_{i,t}^{S} - \mu_i^{S}}{\sigma_i^{S}}$, $\widetilde{IL_{i,t}^{A}} = \frac{IL_{i,t}^{A} - \mu_i^{A}}{\sigma_i^{A}}$, and $\widetilde{IL_{i,t}^{T}} = \frac{IL_{i,t}^{T} - \mu_i^{T}}{\sigma_i^{T}}$. μ_i and σ_i are the corresponding time-series mean and standard deviation of firm i's liquidity measured by the three methods discussed above. All the matrix calculations and APC approach implementations are processed by MATLAB and the code is available from the authors upon request.

A.2 Examples of the momentum factors and related adjustments

We use an example to illustreat the the *first* momentum factor. For instance, for July 2001, $R_{i,t-1}^{100}$ is the returns earned from investing in stock i on 23 March 2001 for 100 days to sell it on 30 June 2001, which is

$$R_{i,t-1}^{100} = \frac{P_{i,30/06/2001} - P_{i,23/03/2001}}{P_{i,23/03/2001}} \quad (A.6)$$

In contrast, for this instance, the returns specified in Eq. (11) is

$$R_{i,t} = \frac{P_{i,31/07/2001} - P_{i,30/06/2001}}{P_{i,30/06/2001}} \quad (A.7)$$

This example illustrates that $R_{i,t-1}^{100}$ and $R_{i,t}$ have an accounting information link since $P_{i,30/06/2001}$ is embedded commonly in both variables. Therefore, Amihud's $R_{i,t-1}^{100}$ has a flaw in the estimation since it generates an accounting link between $R_{i,t}$ and $R_{i,t-1}^{100}$, so that $R_{i,t-1}^{100}$ can no longer be 'pre-determined' exogenously, creating an endogeneity problem of the first momentum in the estimation.

To address the issue, we amend the computation of $R_{i,t}$ from using the price on the last trading date of the present month less one on the last trading date of the previous month, to using the price on the last trading date of the present month less one on the first date of the present month, for instance,

$$R_{i,t} = \frac{P_{i,31/07/2001} - p_{i,1/07/2001}}{p_{i,1/07/2001}} \quad (A.8)$$

Our amendment indirectly refine Amihud's $R_{i,t-1}^{100}$ in order to avoid the accounting link between $R_{i,t}$ and $R_{i,t-1}^{100}$.

Here we also illustrate an example of the *second* momentum factor. For instance, in July 2002, we count 1/07/2002 as the date 0 of the investment, which gives

$$R_{i,t-3}^{265} = \frac{P_{i,22/03/2002} - P_{i,1/07/2001}}{P_{i,1/07/2001}} \quad (A.9)$$

The stock price on 22/03/2002 is more than three months lagged from the stock price on 1/07/2002, so we regard $R_{i,t-3}^{265}$ as a strict exogenous variable in the estimation as it fails to reject the null hypothesis for the third-order autocorrelation of the disturbance term.

A.3 Spotting outliers in the sample

We conduct a visual check of outliers by plotting the monthly return variable R_{it} against each explanatory variable specified in Eq. (6.1), (6.2), (7.1) and (7.2). With each data plot, there are no individual observations, or a small group of observations found for having an abnormal scatter that could affect the robustness of estimation except the variable of the first difference of the rival average of market liquidity ($\Delta\overline{L}_{jt-1}^{M}$) employed for the estimation of Eq. (7.2). For instance, Germany in the period of 2010-13 is found to have a small group of observations lying far away from the most concentrated scatter range of [-0.15, 0.15]. We compared this small group of the unusual, scattered observations with other normal observations for their effects on the stock returns. We find that the outliers of $\Delta\overline{L}_{jt-1}^{M}$ have no impact on the returns but the sample without the outliers has a significant effect on the returns.

Another example is the US where there are no visually perceived outliers on the scatter chart for $\Delta\overline{L}_{jt-1}^{M}$ in the pre-financial-crisis period. In contrast, there are groups of observations lying far away from the most scattered range of the sample for both the during-crisis period and the post-crisis period, respectively. Interestingly, the outliers of $\Delta\overline{L}_{jt-1}^{M}$ on the scatter are from a particular time period, May and June 2012 in the post-crisis period. This may suggest something unusual happened to the US market during that time. We compared these observed unusual changes in illiquidity with other normal observations for their effects on the stock returns and found our estimated effects consistent across different groups of observations, although the magnitude of each estimate varies across the three samples.

A.4 Full estimation for four countries across three periods.

[Table A.1, A.2, A.3, and A.4]

References

Acharya, Viral V, and Lasse Heje Pedersen. 2005. "Asset pricing with liquidity risk." *Journal of financial Economics* 77 (2): 375-410.

Amihud, Yakov. 2002. "Illiquidity and stock returns: cross-section and time-series effects." *Journal of financial markets* 5 (1): 31-56.

Amihud, Yakov, Allaudeen Hameed, Wenjin Kang, and Huiping Zhang. 2015. "The illiquidity premium: International evidence." *Journal of financial economics* 117 (2): 350-368.

Amihud, Yakov, and Haim Mendelson. 1986. "Asset pricing and the bid-ask spread." *Journal of financial Economics* 17 (2): 223-249.

Amihud, Yakov, and Haim Mendelson. 1991. "Liquidity, asset prices and financial policy." *Financial Analysts Journal* 47 (6): 56-66.

Apergis, Nicholas, Panagiotis G Artikis, and Dimitrios Kyriazis. 2015. "Does stock market liquidity explain real economic activity? New evidence from two large European stock markets." *Journal of International Financial Markets, Institutions and Money* 38: 42-64.

Assefa, Tibebe A, and André Varella Mollick. 2014. "African stock market returns and liquidity premia." *Journal of International Financial Markets, Institutions and Money* 32: 325-342.

Bodie, Z. 2003. *Investments*. 5 ed.*Fifth Edition*: Tata McGraw-Hill Education.

Brennan, Michael J, Tarun Chordia, and Avanidhar Subrahmanyam. 1998. "Alternative factor specifications, security characteristics, and the cross-section of expected stock returns." *Journal of financial Economics* 49 (3): 345-373.

Brennan, Michael J, and Avanidhar Subrahmanyam. 1996. "Market microstructure and asset pricing: On the compensation for illiquidity in stock returns." *Journal of financial economics* 41 (3): 441-464.

Brockman, Paul, Dennis Y Chung, and Christophe Pérignon. 2009. "Commonality in liquidity: A global perspective." *Journal of Financial and Quantitative Analysis* 44 (4): 851-882.

Cakici, Nusret, and Adam Zaremba. 2021. "Liquidity and the cross-section of international stock returns." *Journal of Banking & Finance* 127: 106123.

Carhart, Mark M. 1997. "On persistence in mutual fund performance." *The Journal of finance* 52 (1): 57-82.

Chan, Howard W, and Robert W Faff. 2005. "Asset pricing and the illiquidity premium." *Financial Review* 40 (4): 429-458.

Cheung, William Mingyan, Richard Chung, and Scott Fung. 2015. "The effects of stock liquidity on firm value and corporate governance: Endogeneity and the REIT experiment." *Journal of corporate finance* 35: 211-231.

Chordia, Tarun, Sahn-Wook Huh, and Avanidhar Subrahmanyam. 2009. "Theory-based illiquidity and asset pricing." *The Review of Financial Studies* 22 (9): 3629-3668.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam. 2000. "Commonality in liquidity." *Journal of financial economics* 56 (1): 3-28.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam. 2008. "Liquidity and market efficiency." *Journal of financial Economics* 87 (2): 249-268.

Chordia, Tarun, Avanidhar Subrahmanyam, and V Ravi Anshuman. 2001. "Trading activity and expected stock returns." *Journal of financial Economics* 59 (1): 3-32.

Datar, Vinay T, Narayan Y Naik, and Robert Radcliffe. 1998. "Liquidity and stock returns: An alternative test." *Journal of financial markets* 1 (2): 203-219.

de Menil, Georges. 2010. "Reflections on the Great Recession of 2008–09." *Asian Economic Papers* 9 (3): 162-173.

Dissanaike, Gishan, and Kim-Hwa Lim. 2015. "Detecting and quantifying insider trading and stock manipulation in Asian markets." *Asian Economic Papers* 14 (3): 1-20.

Eleswarapu, Venkat R, and Marc R Reinganum. 1993. "The seasonal behavior of the liquidity premium in asset pricing." *Journal of Financial Economics* 34 (3): 373-386.

Elton, E. J., M. J. Gruber, S. J. Brown, and W. N. Goetzmann. 2014. *Modern portfolio theory and investment analysis*. 9 ed.: John Wiley and Sons.

Eun, Cheol S, and Wei Huang. 2007. "Asset pricing in China's domestic stock markets: Is there a logic?" *Pacific-Basin Finance Journal* 15 (5): 452-480.

Fabre, Joel, and Alex Frino. 2004. "Commonality in liquidity: evidence from the Australian Stock Exchange." *Accounting & Finance* 44 (3): 357-368.

Fama, Eugene F, and Kenneth R French. 1992. "The cross‐section of expected stock returns." *the Journal of Finance* 47 (2): 427-465.

Fama, Eugene F, and James D MacBeth. 1973. "Risk, return, and equilibrium: Empirical tests." *Journal of political economy* 81 (3): 607-636.

Gofran, Ruhana Zareen, Andros Gregoriou, and Lawrence Haar. 2022. "Impact of Coronavirus on liquidity in financial markets." *Journal of International Financial Markets, Institutions and Money* 78: 101561.

Hameed, Allaudeen, Wenjin Kang, and Shivesh Viswanathan. 2010. "Stock market declines and liquidity." *The Journal of finance* 65 (1): 257-293.

Hay, Donald A, and Guy S Liu. 1998. "The investment behaviour of firms in an oligopolistic setting." *The Journal of Industrial Economics* 46 (1): 79-99.

Hirayama, Kenjiro, and Yoshiro Tsutsui. 2013. "International stock price co-movement." *Asian Economic Papers* 12 (3): 157-191.

Huang, Hung-Yi, and Kung-Cheng Ho. 2020. "Liquidity, earnings management, and stock expected returns." *The North American Journal of Economics and Finance* 54: 101261.

Huberman, Gur, and Dominika Halka. 2001. "Systematic liquidity." *Journal of Financial Research* 24 (2): 161-178.

Keene, Marvin A, and David R Peterson. 2007. "The importance of liquidity as a factor in asset pricing." *Journal of Financial Research* 30 (1): 91-109.

Korajczyk, Robert A, and Ronnie Sadka. 2008. "Pricing the commonality across alternative measures of liquidity." *Journal of Financial Economics* 87 (1): 45-72.

Lam, Keith SK, and Lewis HK Tam. 2011. "Liquidity and asset pricing: Evidence from the Hong Kong stock market." *Journal of Banking & Finance* 35 (9): 2217-2230.

Lee, Kuan-Hui. 2011. "The world price of liquidity risk." *Journal of Financial Economics* 99 (1): 136-161.

Leirvik, Thomas, Sondre R Fiskerstrand, and Anders B Fjellvikås. 2017. "Market liquidity and stock returns in the Norwegian stock market." *Finance Research Letters* 21: 272-276.

Lesmond, David A. 2005. "Liquidity of emerging markets." *Journal of financial economics* 77 (2): 411-452.

Luo, Di. 2022. "ESG, liquidity, and stock returns." *Journal of International Financial Markets, Institutions and Money* 78: 101526.

Mancini, Loriano, Angelo Ranaldo, and Jan Wrampelmeyer. 2013. "Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums." *The Journal of Finance* 68 (5): 1805-1841.

Marshall, Ben R, and Martin Young. 2003. "Liquidity and stock returns in pure order-driven markets: evidence from the Australian stock market." *International Review of Financial Analysis* 12 (2): 173-188.

McKibbin, Warwick J, and Andrew Stoeckel. 2010. "The global financial crisis: Causes and consequences." *Asian Economic Papers* 9 (1): 54-86.

Narayan, Paresh Kumar, and Xinwei Zheng. 2011. "The relationship between liquidity and returns on the Chinese stock market." *Journal of Asian Economics* 22 (3): 259-266.

Nguyen, Nhut H, and Ka Hei Lo. 2013. "Asset returns and liquidity effects: Evidence from a developed but small market." *Pacific-Basin Finance Journal* 21 (1): 1175-1190.

Pástor, Ľuboš, and Robert F Stambaugh. 2003. "Liquidity risk and expected stock returns." *Journal of Political economy* 111 (3): 642-685.

Rouwenhorst, K Geert. 1999. "Local return factors and turnover in emerging stock markets." *The journal of finance* 54 (4): 1439-1464.

Sarr, Abdourahmane, and Tonny Lybek. 2002. "Measuring liquidity in financial markets." *IMF Working Paper* 02/232.

Wang, Yuenan, and Amalia Di Iorio. 2007. "The cross section of expected stock returns in the Chinese A-share market." *Global finance journal* 17 (3): 335-349.

Tables and Figures

Table 1. Rank of correlation between each of the three measures of stock illiquidity and commonality of liquidity

Common Factor	IL_{it}^{S}	IL_{it}^{A}	IL_{it}^{T}
Germany (L_{it}^{C})	-0.860	-0.697	-0.622
UK (L_{it}^{C})	-0.948	-0.139	0.273
US (L_{it}^{C})	-0.949	-0.436	-0.835
China (L_{it}^{C})	-0.895	-0.923	-0.864

Figure 1 The movement of the common factor of liquidity (left axis) vs the quoted proportional spread (right axis) over time for Germany, UK, US, and China

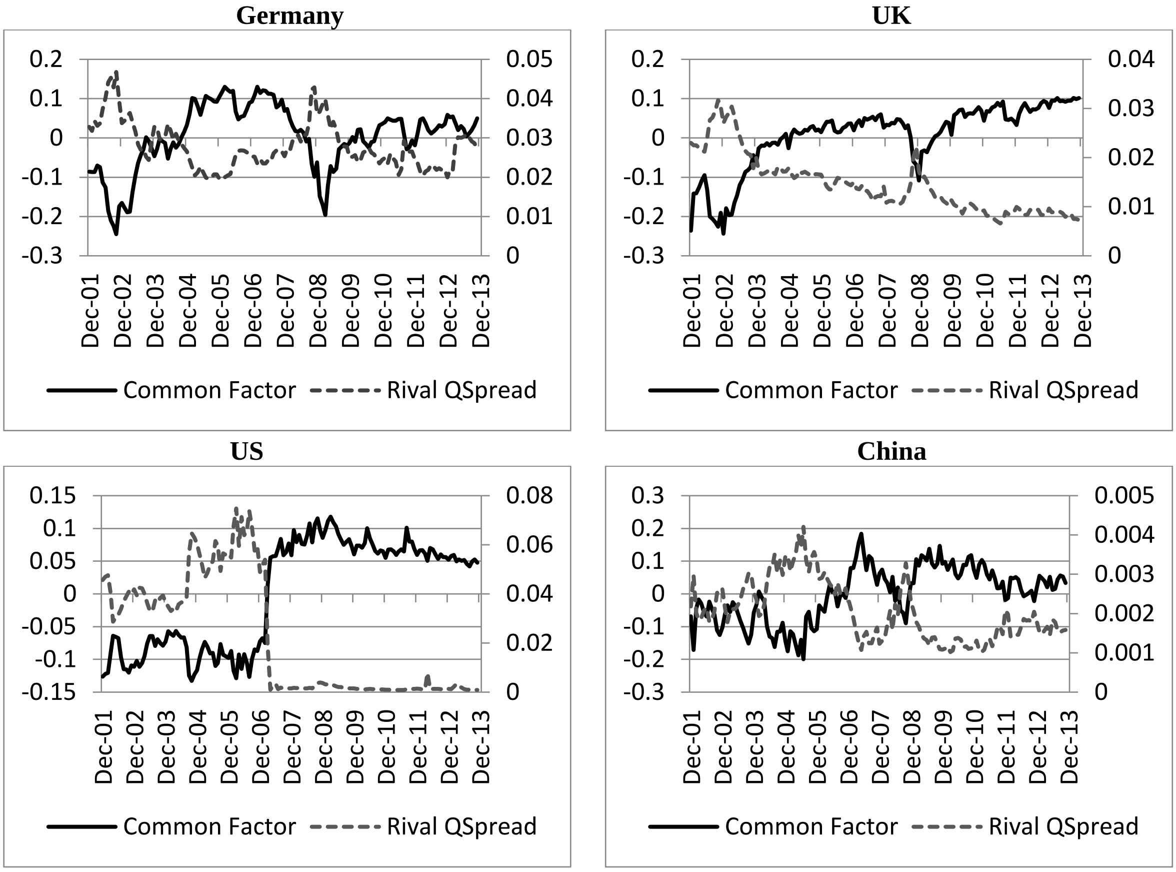

Figure 2 The monthly average stock price: UK, US, Germany and China 2002-2013

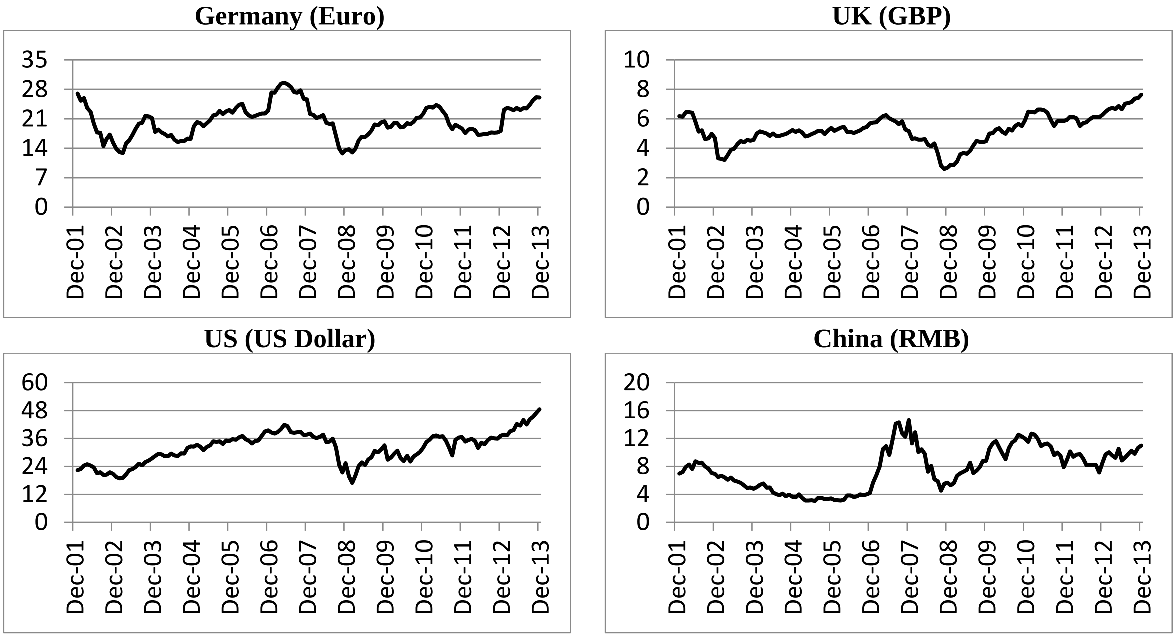

Figure 3 The monthly average stock returns: UK, US, Germany and China 2002-2013

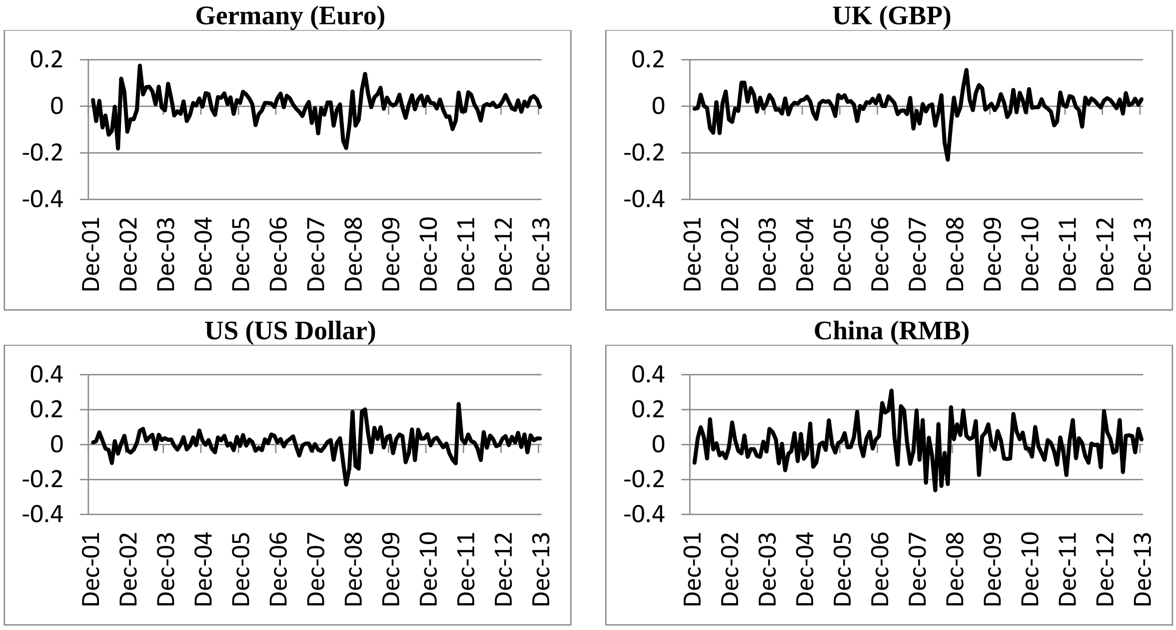

Table 2 Descriptive Statistics of Variables: UK, US, Germany and China

Variable	Germany (EUR), N=59955			UK (GBP), N=59555		
	Mean	P50	SD	Mean	P50	SD
Returns ($R_{i,t}$)	0.004	-0.001	0.135	0.004	0.004	0.11
Mkt illiquidity ($\overline{L}^{M}_{j,t-1}$)	0.028	0.022	0.022	0.015	0.007	0.018
$R^{100}_{i,t-1}$	0.033	0.013	0.27	0.037	0.031	0.218
$R^{265}_{i,t-3}$	0.077	0.011	0.572	0.101	0.07	0.444
Volatility ($V_{i,t-1}$)	0.029	0.024	0.02	0.02	0.017	0.013
Firm Size ($*10^9$)	1.43	0.112	4.13	1.89	0.417	4.89

Variable	US (USD), N=165957			China (RMB), N=150750		
	Mean	P50	SD	Mean	P50	SD
Returns ($R_{i,t}$)	0.01	0.008	0.119	0.008	0	0.137
Mkt illiquidity ($\overline{L}^{M}_{j,t-1}$)	0.022	0.003	0.033	0.002	0.002	0.001
$R^{100}_{i,t-1}$	0.053	0.041	0.243	0.023	-0.016	0.258
$R^{265}_{i,t-3}$	0.113	0.065	0.518	0.1	-0.054	0.585
Volatility ($V_{i,t-1}$)	0.024	0.02	0.017	0.027	0.025	0.011
Firm Size ($*10^9$)	5.17	1.73	9.48	4.67	2.68	6.19

Table 3 The impact of liquidity on stock returns: A summary on estimated λ and θ

	Pre-Crisis: 2002-2006		During-Crisis: 2007-2009		Post-Crisis: 2010-2013	
	Rival average of illiquidity, λ	Common-factor of liquidity, θ	Rival average of illiquidity, λ	Common-factor of liquidity, θ	Rival average of illiquidity, λ	Common-factor of liquidity, θ
Germany						
Stage 1	-0.0731***	0.125***	-0.0627***	0.0674***	0.0783***	-0.384***
	25,448	*25,448*	*16,712*	*16,712*	*17,795*	*17,795*
Stage 2	0.00171	-0.107***	0.0216*	-0.0560*	0.0844***	-0.447***
	25,448	*25,448*	*16,712*	*16,712*	*17,795*	*17,795*
Stage 3	-0.0252	0.358***	-0.0431*	0.204***	-0.143***	-0.100
	24,278	*24,278*	*16,222*	*16,222*	*17,317*	*17,317*
Stage 4	-0.0696***	0.414***	-0.0859***	0.155***	-0.139***	-0.0986
	23,113	*23,113*	*15,346*	*15,346*	*15,862*	*15,862*
Stage 5	-0.0776***	0.428***	-0.0818***	0.118**	-0.137***	-0.0928
	23,113	*23,113*	*15,346*	*15,346*	*15,862*	*15,862*
The UK						
Stage 1	-0.0346***	0.137***	0.0327***	-0.274***	0.0541***	0.0123
	26,515	*26,515*	*15,194*	*15,194*	*17,846*	*17,846*
Stage 2	0.0615***	-0.0315	-0.00097	-0.190***	0.0727***	-0.370***
	26,515	*26,515*	*15,194*	*15,194*	*17,846*	*17,846*
Stage 3	0.00036	0.178***	-0.0951***	0.0609	-0.0509***	0.155***
	25,251	*25,251*	*14,753*	*14,753*	*17,259*	*17,259*
Stage 4	-0.0822***	0.0758**	-0.1000***	0.0705	-0.0760***	0.0867
	23,781	*23,781*	*14,301*	*14,301*	*15,924*	*15,924*
Stage 5	-0.0899***	0.0956***	-0.105***	0.133**	-0.0703***	0.0656
	23,781	*23,781*	*14,301*	*14,301*	*15,924*	*15,924*
The US						
Stage 1	0.0599***	-0.291***	0.00563***	-0.196***	0.0271***	-1.467***
	70,016	*70,016*	*39,478*	*39,478*	*56,463*	*56,463*
Stage 2	0.0735***	-0.389***	-0.00065	-0.0586***	0.0158***	-1.173***
	70,016	*70,016*	*39,478*	*39,478*	*56,463*	*56,463*
Stage 3	0.0172***	-0.0474**	-0.0665***	-0.824***	-0.0216***	-2.436***
	67,196	*67,196*	*38,522*	*38,522*	*55,344*	*55,344*
Stage 4	0.0252***	-0.0728***	-0.0699***	-1.194***	-0.0230***	-2.790***
	62,803	*62,803*	*35,214*	*35,214*	*50,700*	*50,700*
Stage 5	0.0235***	-0.0602***	-0.0751***	-1.176***	-0.0226***	-2.867***
	62,803	*62,803*	*35,214*	*35,214*	*50,700*	*50,700*
China						
Stage 1	-0.0327***	0.135***	-0.0602***	0.574***	0.0926***	-0.453***
	49,539	*49,539*	*34,013*	*34,013*	*67,198*	*67,198*
Stage 2	0.0204***	-0.0667***	0.0646***	-0.249***	0.183***	-0.929***
	49,539	*49,539*	*34,013*	*34,013*	*67,198*	*67,198*
Stage 3	0.0328***	-0.0541***	0.273***	-0.654***	0.0914***	-0.399***
	46,968	*46,968*	*32,621*	*32,621*	*64,790*	*64,790*
Stage 4	0.0890***	-0.238***	0.308***	-0.684***	0.107***	-0.702***
	43,766	*43,766*	*30,272*	*30,272*	*61,174*	*61,174*
Stage 5	0.0886***	-0.226***	0.252***	-0.558***	0.123***	-0.771***
	43,766	*43,766*	*30,272*	*30,272*	*61,174*	*61,174*

Notes: ***, **, * represent significance at the 1%, 5%, 10% respectively. The reported figures are the estimated λ as the marginal return effect of market illiquidity and estimated θ as the marginal return effect of market liquidity, and the number of observations used for the estimation. Stage 1: Without control of macro shocks. Stage 2: Control of macro shocks by year dummy. Stage 3: Control macro shock and multicollinearity. Stage 4: Control macro shock and multicollinearity and January effect. Stage 5: Control macro shock and multicollinearity, January effect and instrumental $R_{i,t-1}^{100}$.

Table A.1 Germany: The full estimation of market liquidity on stock returns over three periods

Germany Exclude January	**Pre-Crisis**		**During-Crisis**		**Post-Crisis**	
	Stock Returns ($R_{i,t}$)		**Stock Returns ($R_{i,t}$)**		**Stock Returns ($R_{i,t}$)**	
mkt illiquidity, λ	-0.0696***		-0.0859***		-0.139***	
($\Delta\bar{L}^M_{jt-1}$)	(-4.0)		(-3.5)		(-7.2)	
mkt liquidity, θ		0.414***		0.155***		-0.0986
(ΔL^C_{t-1})		(9.5)		(3.4)		(-1.5)
Size ($LnS_{i,t-1}$)	-0.0659***	-0.0667***	-0.0772***	-0.0776***	-0.0451***	-0.0451***
	(-13.7)	(-13.7)	(-12.0)	(-12.0)	(-9.8)	(-9.9)
$R^{100}_{i,t-1}$	0.0124***	0.00876*	0.000423	0.000384	-0.00168	0.00267
	(2.7)	(1.9)	(0.06)	(0.05)	(-0.2)	(0.4)
$R^{265}_{i,t-3}$	0.00454**	0.00549***	-0.00387	-0.00448	0.00515**	0.00490**
	(2.1)	(2.6)	(-0.9)	(-1.0)	(2.1)	(2.0)
Volatility ($V_{i,t-1}$)	-0.0209	-0.00856	-0.0614	-0.0807	-0.204	-0.260*
	(-0.2)	(-0.1)	(-0.5)	(-0.6)	(-1.4)	(-1.8)
Constant	1.271***	1.285***	1.455***	1.465***	0.878***	0.877***
	(13.7)	(13.7)	(12.2)	(12.1)	(9.9)	(10.0)
Observations	23,113	23,113	15,346	15,346	15,862	15,862
$\overline{R^2}$	0.0839	0.0865	0.0847	0.0847	0.0581	0.0546
F-statistic	88.79***	90.72***	98.29***	95.60***	46.27***	41.42***
$\hat{R}^{100}_{i,t-1}$: H (χ^2)	1.06	0.1	4.93	7.84	0	0.11
Years: LR (χ^2)	305.41***	210.02***	387.64***	230.27***	103.24***	130.65***
Firms: H (χ^2)	1137.59***	1108.25***	758.7***	754.43***	629.07***	622.68***

Notes: Figures in bracket are t-statistic. ***, **, * represent significance at the 1%, 5%, 10% respectively. The estimations are made on the basis of the model (7.1) and (7.2), using Least Square Dummy Variable panel estimation technique. The dependent variable is stock returns defined in Eq. (11). The firm specific effects and the annual macroeconomic shocks are controlled by firm and year dummies respectively. We use the first difference variable of market illiquidity and liquidity to estimate the liquidity impact on the returns in order to mitigate the multicollinearity effect. The refined $R^{100}_{i,t-1}$ is used for estimation if the Hausman statistic ($\hat{R}^{100}_{i,t-1}$: H (χ^2)) is not significant in testing the presence of the autocorrelation of $R^{100}_{i,t-1}$ to R_{it}. Otherwise, if it is significant, the instrumental $R^{100}_{i,t-1}$ predicted by $R^{100}_{i,t-2}$ will be employed for estimation. 'Years: LR (χ^2)' means that the Loglikelihood Ratio statistic is used to test the year dummies that capture the effect of the macro shocks to the returns. 'Firms: H (χ^2)' means that the Hausman statistic is applied to test the firm specific effects on the returns in order to justify the use of the fixed-effect panel data model for estimation. We reprint the model (7.1) and (7.2) below:

$$R_{i,t} = \alpha + \lambda\Delta\bar{L}^M_{j,t-1} + b_1 LnS_{i,t-1} + b_2 R^{100}_{i,t-1} + b_3 R^{265}_{i,t-3} + b_4 V_{i,t-1} + F_i + Y_T + \varepsilon_{i,t}$$

$$R_{i,t} = \alpha + \theta\Delta L^C_{t-1} + b_1 LnS_{i,t-1} + b_2 R^{100}_{i,t-1} + b_3 R^{265}_{i,t-3} + b_4 V_{i,t-1} + F_i + Y_T + \varepsilon_{i,t}$$

Table A.2 The UK: The full estimation of market liquidity on stock returns over three periods

UK Exclude January	**Pre-Crisis**		**During-Crisis**		**Post-Crisis**	
	Stock Returns ($R_{i,t}$)		**Stock Returns ($R_{i,t}$)**		**Stock Returns ($R_{i,t}$)**	
mkt illiquidity, λ	-0.0822***		-0.1000***		-0.0760***	
($\Delta\bar{L}^{M}_{jt-1}$)	(-6.5)		(-5.4)		(-6.2)	
mkt liquidity, θ		0.0956***		0.0705		0.0867
(ΔL^{C}_{t-1})		(3.3)		(0.9)		(1.4)
Size ($LnS_{i,t-1}$)	-0.0585***	-0.0552***	-0.0796***	-0.0787***	-0.0589***	-0.0591***
	(-13.6)	(-13.2)	(-10.7)	(-10.5)	(-12.0)	(-12.1)
$R^{100}_{i,t-1}$	0.00945*	0.00261	0.0120	0.0149**	-0.0223***	-0.0181***
	(1.7)	(0.3)	(1.6)	(2.0)	(-3.6)	(-3.0)
$R^{265}_{i,t-3}$	-0.00110	-0.00243	-0.00651*	-0.00621	0.00997***	0.0103***
	(-0.4)	(-0.9)	(-1.7)	(-1.6)	(3.2)	(3.3)
Volatility ($V_{i,t-1}$)	0.228**	0.191*	-0.394**	-0.476***	0.0976	0.0554
	(2.1)	(1.8)	(-2.141)	(-2.6)	(0.7	(0.4)
Constant	1.170***	1.106***	1.602***	1.590***	1.221***	1.229***
	(13.6)	(13.3)	(10.8)	(10.7)	(12.1)	(12.2)
Observations	23,781	23,781	14,301	14,301	15,924	15,924
$\overline{R^2}$	0.068	0.066	0.090	0.088	0.050	0.047
F-statistic	77.48***	75.12***	108.8***	110.0***	39.45***	38.82***
$\hat{R}^{100}_{i,t-1}$: H (χ^2)	1.64	15.52**	2.5	3.8	7.03	5.98
Years: LR (χ^2)	618.19***	525.27***	419.74***	418.86***	192.54***	359.92***
Firms: H (χ^2)	1051.45***	880.94***	818.54***	796.6***	856.08***	849.18***

Note: see the note for Table A.1.

Table A.3 The US: The full estimation of market liquidity on stock returns over three periods

US Exclude January	Pre-Crisis		During-Crisis		Post-Crisis	
	Stock Returns ($R_{i,t}$)		Stock Returns ($R_{i,t}$)		Stock Returns ($R_{i,t}$)	
mkt illiquidity, λ	0.0235***		-0.0751***		-0.0226***	
($\Delta\bar{L}^{M}_{jt-1}$)	(7.4)		(-25.1)		(-10.2)	
mkt liquidity, θ		-0.0728***		-1.176***		-2.867***
(ΔL^{C}_{t-1})		(-3.3)		(-24.5)		(-49.4)
Size ($LnS_{i,t-1}$)	-0.0480***	-0.0494***	-0.151***	-0.149***	-0.0775***	-0.0744***
	(-19.6)	(-19.5)	(-26.7)	(-26.6)	(-23.0)	(-22.7)
$R^{100}_{i,t-1}$	-0.00697	0.00388	0.0798***	0.0720***	-0.00914*	0.0273***
	(-1.4)	(1.3)	(14.2)	(13.0)	(-1.7)	(5.1)
$R^{265}_{i,t-3}$	-0.00168	-0.00144	0.0249***	0.0196***	0.00419***	0.00696***
	(-0.9)	(-0.8)	(10.6)	(8.4)	(3.7)	(5.6)
Volatility ($V_{i,t-1}$)	0.275***	0.296***	-0.306***	-0.364***	-0.449***	0.0583
	(3.9)	(4.2)	(-3.7)	(-4.4)	(-6.8)	(0.9)
Constant	1.040***	1.068***	3.221***	3.180***	1.707***	1.628***
	(19.7)	(19.7)	(26.7)	(26.7)	(23.4)	(23.0)
Observations	62,803	62,803	35,214	35,214	50,700	50,700
$\overline{R^2}$	0.048	0.048	0.135	0.128	0.039	0.101
F-statistic	149.5***	141.4***	473.6***	535.3***	96.64***	379.8***
$\hat{R}^{100}_{i,t-1}$: H (χ^2)	19.16**	10.17	43.13***	17.45***	21.39***	25.37***
Years: LR (χ^2)	831.23***	1342.56***	225.75***	164.06***	623.98***	113.31***
Firms: H (χ^2)	1790.46***	2038.38***	2729.24***	2520.38***	2281.4***	2134.29***

Note: see the note for Table A.1.

Table A.4 China: The full estimation of market liquidity on stock returns over three periods

China Exclude January	**Pre-Crisis** Stock Returns ($R_{i,t}$)		**During-Crisis** Stock Returns ($R_{i,t}$)		**Post-Crisis** Stock Returns ($R_{i,t}$)	
mkt illiquidity, λ	0.0886***		0.252***		0.123***	
($\Delta \bar{L}^{M}_{jt-1}$)	(22.0)		(50.6)		(27.9)	
mkt liquidity, θ		-0.226***		-0.558***		-0.771***
(ΔL^{C}_{t-1})		(-17.6)		(-32.1)		(-36.8)
Size ($LnS_{i,t-1}$)	-0.0712***	-0.0740***	-0.265***	-0.273***	-0.120***	-0.117***
	(-22.7)	(-23.5)	(-50.3)	(-49.7)	(-24.8)	(-24.8)
$R^{100}_{i,t-1}$	0.0338***	0.0356***	0.151***	0.157***	0.00833	0.00471
	(6.1)	(6.4)	(21.4)	(21.7)	(1.4)	(0.8)
$R^{265}_{i,t-3}$	0.0353***	0.0362***	0.0547***	0.0607***	0.0429***	0.0394***
	(12.9)	(13.1)	(24.5)	(26.0)	(21.5)	(20.0)
Volatility ($V_{i,t-1}$)	0.668***	0.676***	-0.142	0.747***	1.438***	1.490***
	(9.8)	(9.9)	(-1.3)	(7.0)	(20.5)	(21.6)
Constant	1.502***	1.560***	5.856***	5.980***	2.619***	2.554***
	(22.9)	(23.7)	(51.3)	(50.3)	(24.8)	(24.8)
Observations	43,766	43,766	30,272	30,272	61,174	61,174
$\overline{R^2}$	0.0558	0.0547	0.279	0.258	0.0842	0.091
F-statistic	340.4***	288.2***	1947***	1416***	600.5***	723.9***
$\hat{R}^{100}_{i,t-1}$: H (χ^2)	36.05***	355.2***	252.64***	79.41***	1363.14***	936.27***
Years: LR (χ^2)	812.03***	763.08***	3137.31***	2509.75***	1663.27***	1891.87***
Firms: H (χ^2)	1445.34***	1532.19***	4784.95***	4879.75***	2972.68***	2902.11***

Note: see the note for Table A.1.