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Which Market Enhances Market Efficiency from Liquidity? Evidence of Stock Liquidity in Relation to Market Value

Guy Liu
Peking University HSBC Business School
liusj@phbs.pku.edu.cn

Jinke Li
School of Economics
Swansea University
jinke.li@swanksea.ac.uk

Andros Gregoriou
Brighton Business School
University of Brighton, BN2 4AT, UK
a.gregoriou@brighton.ac.uk

Yibo Bo
Brunel University Economics Department

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 of 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 relation 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.

Key words: 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 investment from less effective 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 investment of firms for improvement of corporate control and governance (Cheung et al, 2015), and good governance attracts more investors (Di, 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 of stock liquidity to the 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 & 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 the firm-level estimation. Amihud and Mendelson (1986) introduced 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). In the study of illiquidity return premiums using Amihud (2002) to measure illiquidity, 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 & 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) and Liu (2013). 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), Pastor and Stamburgh (2003), Acharya and Pederson (2005), Wang and Di (2007), Lee (2011), and Lam et al (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) employed 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 literature finds 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 the 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 to observe the positive pattern of liquidity in relation to stock returns, reflecting market efficiency.

In view of the above, an empirical pattern of the relationship on a market over time becomes an interesting research question, since it can indicate if 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 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. 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 to three sub-periods according to the pre financial crisis (2002-2006), during the financial crisis (2007-2009) and post financial crisis (2010-2013), which helps perform comparative analysis across time for each market.

One challenge in using market liquidity to estimate its effect on stock returns is how to measure market liquidity. Most of the previous literature takes either the average method or the common factor approach to compute the market liquidity. In this context, our study takes both methods in order to compare the consistency of estimation from two measures. 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 captures information related to co-variation of liquidity across stocks and measures, which is called "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, 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.

For the second approach to measure market liquidity, we average the liquidity of all stocks excluding one 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 derive a market liquidity that 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.

There are many liquidity measures discussed in literature, however the three that are most applied are the following. The Amihud illiquidity ratio for capturing the price-based measures, the Quoted Proportional Spread of illiquidity for the transaction-cost-based measures, and the Turnover Ratio for the volume-based measures. This study takes these three measures to calculate the monthly average liquidity of each individual stock respectively, and then applies the APC (Korajczyk and Sadka, 2008) to extract factors embedded commonly across both measures and stocks. Given that the Quoted Spread of illiquidity exhibits the highest correlation to the commonality factor among the three liquidity measures, we choose the Quoted Spread as the liquidity measure to calculate the rival average of the market illiquidity for our study.

In estimation of the returns and liquidity relationship, one common issue is the misspecification of the models in estimation by omitting the control of macroeconomic conditions and policy shocks. Without the control, the 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) finds 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, the US as the largest stock market in the world, 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 value liquidity and are more efficient. Some 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 Measure of Market Liquidity

2.1 Specification of Estimation Models

To investigate the stock returns effect of market liquidity, most empirical studies follow a time-series model introduced by Amihud (2002):

$$R_t - R_{ft} = a_0 + \theta L_{t-1} + \rho L_t^{UN} + \boldsymbol{b}\boldsymbol{X_{t-1}} + \varepsilon_t \quad \ldots \ldots . \ldots \ldots \ldots \ldots \ldots (1)$$

Where R_t is the market average stock return of listed firms in month *t*. $R_{ft}$is the risk free rate in month *t*. L_{t-1} and L_t^{UN} are the lagged and unexpected stock market liquidity in month *t-1* and month *t*, respectively. $\boldsymbol{X_{t-1}}$ is a vector of other controlling variables that can affect stock returns. The impact of market liquidity on the market returns is measured by the coefficient θ .

The above model 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 (${L^C}_{t-1}$), extracted by the APC Method (Korajczyk and Sadka , 2008) for a market:

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

Furthermore, we can expand the time-series-based model in equation (2) to a panel-data estimation model (named the Amihud Commonality-Factor Panel Estimation Model) to investigate the market liquidity effect on firm-level stock returns, by estimating the model below:

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

Where R_{it} is the returns of stock *i* in month *t*, and $\boldsymbol{X_{it-1}}$ is a vector of one-month lagged firm characteristic variables that control other effects on stock returns, and these variables are similar to those applied by Amihud (2002). F_i and ε_{it} are firm dummies and the error term, respectively. Pu (2009) compute Equation (3) without control of the firm fixed effects and find that there is a significant liquidity commonality factor impact on the unexplained portion of credit spread changes and returns. Korajczyk and Sadka (2008) also apply model (3) to estimate the impact of the common factor liquidity to stock returns.

To test the robustness of the Amihud Commonality-Factor Panel Estimation Model of (3), we introduce a new approach to measure market liquidity, which is defined as follows:

$$\overline{L}_{jt}^M = \left(\frac{\sum_{i=1}^N L_{it} - L_{it}^M}{N-1} \right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

Where, using the liquidity measure M, $\overline{L}_{jt}^M$ averages its liquidity of all stocks on the market by excluding the concerning firm *i* with *–i denoting i excluded* at time t, and *j= -i* in (4). N is the number of trading days in month t. Since stock i is excluded from the computation, we call the average as the rival average of liquidity for stock i. This idea 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. To test the robustness of estimation of the L^{C}_{t-1} in (3), we replace it with $\overline{L}^{M}_{-it}$ to obtain the model in equation (5):

$$R_{it} = a_0 + \lambda \overline{L}^{M}_{jt} + \boldsymbol{bX_{it-1}} + F_i + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

The rival average of liquidity $\overline{L}^{M}_{jt}$ brings two advantages in the estimation of equation (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 $\overline{L}^{M}_{jt}$ as exogenous in relation to the estimation of the returns R_{it} since $\overline{L}^{M}_{jt}$ excludes information of stock i. In prior research, the endogeneity issue in the regression of the averaging liquidity of all stocks to the corresponding stock returns has been identified (see among others, Amihud and Mendelson (1986), Amihud (2002) and Hameed et al (2010)). We believe that the rival average can specifically help avoid the endogenous problem in estimation without compromising its representativeness to the market average when the sample is large.

Furthermore, in estimation of the market liquidity effect on the returns, one particular problem is that market liquidity and macroeconomic shocks can often be disturbed, causing a model misspecification problem that will result in biased estimation of the market liquidity on the returns if the control of the shocks is omitted in estimation. In order to separate the liquidity effect from macroeconomic shocks, we introduce a time dummy in the estimation of model (3) and (5):

$$R_{it} = a_0 + \theta L^{C}_{t-1} + \boldsymbol{bX_{it-1}} + F_i + D_T + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6.1)$$

$$R_{it} = a_0 + \lambda \overline{L}^{M}_{jt-1} + \boldsymbol{bX_{it-1}} + F_i + D_T + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6.2)$$

Where, D_T is a time dummy to control the effect of macroeconomic shocks that can usually last over a year T. To mitigate the effect of the multicollinearity between the year dummy and the market liquidity in the estimation of (6.1) and (6.2), we replace the level-based L_{t-1}^{C} or $\overline{L}_{jt-1}^{M}$ with their first difference of ΔL_{t-1}^{C} and $\Delta\overline{L}_{jt-1}^{M}$, respectively, see below:

$$R_{it} = a_0 + \theta \Delta L_{t-1}^{C} + \boldsymbol{bX_{it-1}} + F_i + D_T + \varepsilon_{it} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (7.1)$$

$$R_{it} = a_0 + \lambda\, \Delta\overline{L}_{jt-1}^{M} + \boldsymbol{bX_{it-1}} + F_i + D_T + \varepsilon_{it} \quad \dots\dots\dots\dots\dots\dots\dots\dots (7.2)$$

Having controlled both stock/firm specific effects and macro shocks, the estimation of model (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 model (3) and (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 from 2002 to 2006, the during-crisis period between 2007 and 2009, and the post-crisis period from 2010 to 2013. In addition, the January effects emphasized by both Eleswarapu and Reinganum (1993) and Amihud (2002) are also taken into account in our empirical estimations.

2.2 Specification of variables in estimation

Market Liquidity

In estimation of the return-liquidity models discussed above, the market liquidity is a key variable, which we will compute in two stages. Stage one measures individual stock liquidity and stage two aggregates individual stock liquidity to a market level. We convert individual stock liquidity to a market level through two approaches. The commonality factor of liquidity (L_t^C) and the rival average of liquidity ($\overline{L}_{jt}^{M}$), which we will discuss in turn below.

Stage one: measure individual stock liquidity

Although there are many ways to measure liquidity at a stock level in the academic literature, they can be classified according to three major approaches. Transaction-cost-based measure, Volume-based measure and Price-based measure. Our research takes the Quoted Proportional Spread of illiquidity as the transaction-cost-based measure, the Amihud illiquidity Ratio (2002) as the price-base measure, and the turnover ratio of liquidity as the volume-base measure for computing individual stock liquidity, respectively.

For the transaction-cost based measure, we follow Amihud and Mendelson (1986) and Eleswarapu and Reinganum (1993) by defining the monthly average of the Quoted Proportional Spread measure of illiquidity as follows:

$$IL_{it}^{S} = \frac{1}{N}\sum_{\tau=1}^{N}\frac{2\left(P_{i\tau}^{A}-P_{i\tau}^{B}\right)}{P_{i\tau}^{A}+P_{i\tau}^{B}} \quad with\ 0 < IL_{i\tau}^{S} < 1 \dots\dots\dots\dots\dots \ (8)$$

Where IL_{it}^{S} is illiquidity measured by the Quoted Proportional Spread of stock *i* in month *t*. $P_{i\tau}^{A}$ 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*. Higher Quoted Proportional Spread represents lower liquidity.

For the price-based measure, we follow the Amihud (2002) illiquidity ratio which has been widely applied to define the monthly average Amihud Illiquidity Ratio as follows:

$$IL_{it}^{A} = \frac{1}{N}\sum_{\tau=1}^{N}\frac{|R_{i\tau}|}{VOLD_{i\tau}} \quad with\ 0 \le IL_{i\tau}^{A} < 1 \ \dots\dots\dots\dots\dots\dots\dots (9)$$

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

For the volume-base measure, we take the turnover ratio that is widely applied in previous research, see Rouwenhorst (1999), Jones (2002), Chan and Faff (2005), and Koch (2010)), which is defined as follows:

$$L_{it}^{T} = \frac{1}{N} \sum_{\tau=1}^{N} \frac{Q_{i\tau}}{S_{i\tau}} \quad with\, 0 \leq L_{i\tau}^{T} \leq 1 \quad \ldots\ldots\ldots\ldots\ldots.. \ (10)$$

Where L_{it}^{T} is Turnover Ratio of stock i in month t. $Q_{i\tau}$ 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. Higher Turnover Ratio represents higher stock liquidity. Moreover, in order to maintain all the three liquidity measures to represent illiquidity to make direct comparison more straightforward, we reverse the Turnover Ratio using the expression $IL_{it}^{T} = 1 - L_{it}^{T}$.

Stage Two: measure market liquidity

Common Factor of Liquidity

With a large sample of data, 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 $\boldsymbol{L^C} = [L_1^C,\ L_2^C, \ldots L_{t-1}^C,\ L_t^C]'$ for each month of a market by solving

$$(\boldsymbol{\eta}^{*}\boldsymbol{I} - \boldsymbol{\Omega}^{\boldsymbol{q}})\boldsymbol{L}^{\boldsymbol{c}} = 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(11)$$

where $\boldsymbol{I}$ is an $K*K$ identity matrix, and K has 144 months of the sample from January 2002 to December 2013. $\boldsymbol{\eta}^{*}$ is the largest eigenvalue of $\boldsymbol{\eta}$ solved from the equation below:

$$|\boldsymbol{\eta I} - \boldsymbol{\Omega}^{\boldsymbol{q}}| = \boldsymbol{0} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(12)$$

where the matrix $\boldsymbol{\Omega}^{\boldsymbol{q}}$ is specified below:

$$\boldsymbol{\Omega^q} = \frac{\boldsymbol{IL^{q\prime} IL^q}}{\boldsymbol{M' M}} \quad \text{.....................................(13)}$$

Where $\boldsymbol{IL^{q\prime}}$ and $\boldsymbol{M'}$ are a transpose of the matrix $\boldsymbol{IL^q}$ and $\boldsymbol{M}$, respectively. $\boldsymbol{M}$ is $N*K$ matrix that can assist with the issue of missing data. N contains all stocks for a market over our three liquidity measurements. $\boldsymbol{IL^q}$ as a matrix that stacks up three liquidity measures defined as follows.

$$\boldsymbol{IL^q} = \begin{bmatrix} \widetilde{IL^S_{\iota,1}} & \cdots & \widetilde{IL^S_{\iota,t}} \\ \vdots & \ddots & \vdots \\ \widetilde{IL^S_{n,1}} & \cdots & \widetilde{IL^S_{n,t}} \\ \widetilde{IL^A_{\iota,1}} & \cdots & \widetilde{IL^A_{\iota,t}} \\ \vdots & \ddots & \vdots \\ \widetilde{IL^A_{n,1}} & \cdots & \widetilde{IL^A_{n,t}} \\ \widetilde{IL^T_{\iota,1}} & \cdots & \widetilde{IL^T_{\iota,t}} \\ \vdots & \ddots & \vdots \\ \widetilde{IL^T_{n,1}} & \cdots & \widetilde{IL^T_{n,t}} \end{bmatrix} \quad \text{...............................(14)}$$

Where, $\widetilde{IL^S_{\iota,t}} = \frac{IL^S_{i,t} - \mu^S_i}{\sigma^S_i}$, $\widetilde{IL^A_{\iota,t}} = \frac{IL^A_{i,t} - \mu^A_i}{\sigma^A_i}$, and $\widetilde{IL^T_{\iota,t}} = \frac{IL^T_{i,t} - \mu^T_i}{\sigma^T_i}$. $IL^S_{i,t}$ is the monthly average of firm i's illiquidity measured by the Quoted Proportional Spread specified in equation (8) for month t, and μ^S_i and σ^S_i are the corresponding time-series mean and standard deviation of firm i's liquidity measured by the Quoted Proportional Spread over the whole sample period. For the same analogy, $IL^A_{i,t}$ is the monthly average of firm i's illiquidity measured by the Amihud illiquidity Ratio specified in (9), and $IL^T_{i,t}$ is the reversed Turnover Ratio of liquidity specified in (10). All the matrix calculations and APC approach implementations are processed by MATLAB.[1]

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 equations (4) and (5) above. Here, our discussion focuses on which measure we shall select from

[1] The MATLAB code used to construct the matrix in equation 14 is available from the authors upon request.

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_{it}^{C}) derived from the common co-variation of the three measures, and then select the one with the highest rank: $Corr\left[IL_{it}^{S}, L_{it}^{C}\right]$, $\mathrm{Corr}\left[IL_{it}^{A}, L_{it}^{C}\right]$ and $Corr\left[IL_{it}^{T}, L_{it}^{C}\right]$. This is because the highest correlation implies the measure that can be the best representable for the commonality factor, and therefore providing us with expectation for the strong consistency in using either of the two market liquidity measures to estimate the returns-and-liquidity relationship. Table 1 below shows the Quoted Proportional Spread of illiquidity (IL_{it}^{S}) that has the highest rank of the correlation.

Furthermore, we also plot both IL_{it}^{S} and L_{it}^{C} for their movement against time. Interestingly, the movement of the market illiquidity versus the market liquidity is highly mirrored with each other in Figure 1, enhancing our expectation of the consistency between the two measurements of market liquidity.

In short, on the basis of discussion above, we select the quoted spread of illiquidity to compute the rival average of illiquidity in equation (4) for estimation.

[INSERT TABLE 1 AND FIGURE 1 HERE]

Other Variables

<u>Monthly stock returns</u>

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

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots(15)$$

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

The volatility variable for risk control

In the academic 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. On this basis, we include the volatility of stock returns denoted by V_{it} as one of the control variables for 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 below:

$$V_{it} = \sqrt{\frac{1}{N}[(R_{i\tau} - \overline{R_{it}})^2 + (R_{i\tau+1} - \overline{R_{it}})^2 + \cdots + (R_{i\tau+N-1} - \overline{R_{it}})^2]} \dots \dots \dots \dots (16)$$

Where *N* is the number of trading days of stock *i* in month *t*, and $R_{i\tau}$ is the stock return of firm i at the first trading day τ in month *t*, and $\overline{R_{it}}$ is the monthly average daily returns of firm *i* in month *t*. We use the volatility to control the risk effect in 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 and 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).

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 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 the small to large companies. In line with these arguments, we control the effect of the firm size in 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_{it}. 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).

The variable for control of the momentum effects

The first momentum R_{it-1}

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 have been applied by Amihud (2002) for estimation of the returns-liquidity relationship. Following Amihud (2002), we define $R100_{it-1}$ as the variable of 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. For instance, if t=July 2001, then $R100_{it-1}$ will be the returns earned from investing in stock i on 23 March 2001 for 100 days to sell it on 30 June 2001, which is $R100_{it-1}= [P_{i\ 30/06/2001} - P_{i\ 23/03/2001}] / P_{i\ 23/03/2001}$. In contrast, for this instance, the returns specified in equation (14) is $R_{it} = \frac{P_{i\,31/07,2001} - P_{i\,30/06,2001}}{P_{i\,30/06,2001}}$. This example illustrates that $R100_{it-1}$ and R_{it} have an accounting information link since $P_{i\ 30/06/2001}$ is embedded commonly in both variables. Amihud's $R100_{it-1}$ has a flaw in estimation since it generates an accounting link between R_{it} and $R100_{it-1}$. The link implies that $R100_{it-1}$ can no longer be 'pre-determined' exogenously, creating an endogeneity problem of the first momentum in estimation.

To address the issue, either we can refine Amihud $R100_{it-1}$ by changing the investment return window from [-100, -1] to [-100,-2] with the first trading day of month t as 0, for instance, $R100_{it-1} = \frac{P_{i\,29/06,2001} - P_{i\,23/03,2001}}{P_{i\,23/03,2001}}$. Alternatively, instead of changing $R100_{it-1}$, we can amend the computation of R_{it} 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, $R_{it} = \frac{p_{i31/07,2001} - p_{i1/07,2001}}{p_{i1/07,2001}}$. We take the latter approach to indirectly refine Amihud $R100_{it-1}$ in order to avoid the accounting link between R_{it} and $R100_{it-1}$.

Furthermore, if the stock price on the first date of month t and the price on the last date of month t-1, such as $P_{1/07/2002}$ and $P_{30/06/2002}$, are auto-correlated, this may cause a dynamic relation of the refined $R100_{it-1}$ to R_{it}, although the two variables are not same in terms of their structure. These possible dynamics could create an endogenous issue for the refined $R100_{it-1}$ if the first-order autocorrelation of the disturbance term appears in estimation. To take this argument into account, we instrument the refined $R100_{it-1}$ using $R100_{it-2}$ with an underlying assumption that the second-order autocorrelation of the disturbance term is null in estimation. We estimate θ and λ by using the instrumental variable of the refined $R100_{it-1}$ for (7.1) and (7.2) as our further robust test to the consistency of our estimations.

The second momentum $R265_{it-3}$

Amihud (2002) introduced the second momentum factor 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. For instance, if t is July 2002, then we count 1/07/2002 as the date 0 of the investment, which gives $R265_{it-3} = \frac{P_{i\,22/03,2002} - P_{i\,1/07,2001}}{P_{i\,1/07,2001}}$. Since the stock price on 22/03/2002 is more than three months lagged from the stock price on 1/07/2002, we regard $R265_{it-3}$ as a strict exogenous variable in estimation that cannot 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 the models (6.1), (6.2), (7.1) and (7.2) are $\mathbf{bX} = b_1V_{it-1} + b_2\,LnS_{it-1} + b_3R100_{it-1} + b_4\,R265_{it-3}$.

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 time period from 1 December 2001 to 31 December 2013. We acquire daily information on the seven variables below:

(i) Last Price: the daily closing price.
(ii) Bid Price 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 last price of the stock multiplied by the total number of its shares outstanding.

Daily prices of stocks are in a currency of US dollars for the US listed firms at range from \$1 to \$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).

From the data collection above, we select our sample of company stocks according to the criteria: (1) it is fully paid ordinary shares, or A shares for China. 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. (2) 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 seven 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. After computation, missing observations and outliers are generated, which need to be dealt with. Following existing studies such as Amihud (2002), Korajczyk and Sadka (2008) and Chordia et al (2009), we further edit 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.

Furthermore, we conduct a visual check of outliers by plotting the monthly return variable R_{it} against each explanatory variable specified in (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 (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], see Figure 2. We compared this small group of the unusual, scattered observations with other normal observations for their effects on the stock returns in Table 2. Clearly, the outliers of $\Delta\overline{L}_{jt-1}^{M}$ have no impact on the returns but the robust sample without the outliers has a significant effect on the returns.

[INSERT TABLE 2 AND FIGURE 2 HERE]

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 denoted by '1' in Figure 3. In contrast, there are groups of observations lying far away from the most scattered range of the sample for both the during-crisis period denoted by '2' in Figure 3 and the post-crisis period denoted by '3' in Figure 3, 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 in Table 3 and found our estimated effects consistent across different groups of observations, although the magnitude of each estimate varies across the three samples.

[INSERT TABLE 3 AND FIGURE 3 HERE]

On the basis of our discussion above, we take a robust sample by excluding scattered outliers in order to capture the behavior of the observations that represent more than 90% of the total sample for our estimation. In the robust sample, we have 440 German company stocks, 425 UK stocks, 1194 US stocks and 1093 Chinese stocks for each of the 144 months from 2002 to 2013.

Our robust sample has 436,217 observations in total for four economies over 144 months. We plot the average stock price and the returns of each country over 144 months in Figure 4 and Figure 5, respectively. The Figures show that each of the four markets has 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 the increase and decrease of the daily stock prices.

[INSERT FIGURES 4 AND 5 HERE]

The mean, median and standard deviation of variables including the stock returns (R_{it}), the rival average of market illiquidity ($\overline{L}_{jt-1}^{M}$), the volatility (V_{it-1}), the firm size (LnS_{it-1}), the refinement of the first momentum ($R100_{it-1}$) and the second momentum ($R265_{it-3}$) are reported for each market in Table 4. As what would be anticipated, 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 most liquid out of the four markets while the German market is 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.

[INSERT TABLE 4 HERE]

4. Estimation and Discussion

To examine an empirical pattern of the relationship between returns and liquidity, we split our data sample of 436,000 observations into three time periods, consisting of the pre-financial crisis, during-crisis and post-crisis respectively for each of the four nations in our sample. We use the common factor of market liquidity and the rival average of market illiquidity, as our comparative strategy to evaluate the robustness and consistency of estimation from these two opposite measures of liquidity. We have five stages of investigation. It starts by estimating models (3) and (5) which have been widely applied in prior research to examine the association between returns and liquidity. The two models are mis-specified since they fail to control for the impact of macroeconomic shocks to stock returns in estimation. The importance of control of macro shocks has been evident clearly by our reported Likelihood Ratio statistic (LR-χ^2), which overwhelmingly rejects the hypothesis that shocks do not have an impact on the returns in estimations. This result holds across Tables 6-9. Furthermore, without the control of the shocks we witness that the estimation of the relationship between returns and liquidity is inconsistent across time periods and samples, from Table 10.

To address this issue, we move onto stage two of our empirical research. We estimate model (6.1) and (6.2) in order to encapsulate the impact of macroeconomic shocks on the association between liquidity and returns. 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. Table 5 reports the correlation between each of the year dummy variables and the liquidity variables for Germany. Some dummies exhibit a correlation with the liquidity as high as 75%, such as Corr[$\bar{L}_{jt-1}^{M}$,YR07]=0.711. In contrast, the first difference of the liquidity variables reduces correlation dramatically, such as Corr[$\Delta\bar{L}_{jt-1}^{M}$,YR07]=0.03. The German example explains the legitimacy of applying model (7.1) and (7.2), that employs the first difference of the liquidity variable for estimation, which is our stage three of our empirical analysis.

[INSERT TABLE 5 HERE]

Furthermore, 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 as our stage four of our empirical analysis, 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 at the presence of the autocorrelation of the first momentum $R100_{it-1}$ to the returns R_{it}, which may be 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 $R100_{it-1}$ by its instrumental variable predicted by $R100_{it-2}$ for estimating (7.1) and (7.2), in order to see if our estimated results from stage three and four can be consistent. The Hausman statistic is employed to test the presence of the dynamic effect on our estimations. In Tables 6 to 9, we report the Hausman statistic. 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.

The full estimation of model (7.1) and (7.2) are displayed in Table 6 for Germany, Table 7 for the UK, Table 8 for the US and Table 9 for China, across the three respective time periods. For the full estimation of other models our reports are provided in Appendix I in order to save space in the main body of the manuscript. All estimations are carried out by the LSDV (Least Square Dummy Variables) panel data estimation technique, controlling both the firm/stock specific effects captured by firm dummies and the macroeconomic shocks captured by year dummies. The instrumental $R100_{it-1}$ will not be applied in estimation unless the significance of Hausman statistic is reported in the Table. The figures in bracket are t-statistics. We summarize findings in Table 6-9 and in Appendix I with a focus on reporting the estimated results of the returns-liquidity relation, λ and θ, in Table 10. We believe the results from Tables 6 to 9 are relatively self-explanatory.

[INSERT TABLES 6-9 HERE]

The summary report displayed in Table 10 allows us to directly compare our 30 estimated empirical relationships across different time periods and estimation methods for each market. In total we have 120 findings for four economies. 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:

The strong evidence of the finding: Both the estimated λ and θ have an opposite and significant sign in affecting the returns for the same time period of a market.

The weak evidence of the finding: One of the estimated λ and θ is significant in the same time period.

The non-conclusive finding: 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 120 findings of the relationship between liquidity and stock returns for each market in turn below.

Germany

The estimated θ and λ in the first row of the Germany Panel of Table 10 are based on model (3) and (5) without controlling for macroeconomic shocks. We also report the number of observations used for the corresponding estimations. The results are not persistently consistent across three time periods. The θ and λ in the second row of Table 10 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 is 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 estimation. For robustness, the estimated θ and λ in the third row are further estimated by dropping the January effect, in which the results in the 4th row are consistent with the estimates in the third row. Furthermore, in the 5th row, we use instrumental $R100_{it-1}$ to replace $R100_{it-1}$ to control for the possible effect of endogeneity in estimation, and the results are very consistent with the estimations in the third and fourth row. Clearly, on the basis of our ranking rules, the comparative estimates of θ and λ shows 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.

The UK

Similarly, the estimated λ and θ in the first and second row of the UK Panel of Table 10 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 shown in the fourth and fifth row 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 row. 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.

The USA

In the third, fourth and fifth row of the US Panel of Table 10, we find that both the estimated λ and θ are significantly opposite with each other, providing strong evidence on the negative effect of liquidity on the returns for the pre-crisis period. The negative relation implies market 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 the group of outliers excluded from our robust sample used for estimation. 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 significant value 0.188 for θ in the during-crisis period. We also witness a significant value of -0.020 for λ and 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 both the observations of the robust sample and the observations of the outlier group, and the inconclusive finding remains.

The difference of 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 and Brennan and Subrahmanyam, 1996), several declare a negative relation (Amihud and Mendelson, 1986 and 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.

China

As the largest emerging market in the world, how does China perceive 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 row of the China Panel of Table 10. The negative relation of the liquidity to the returns can also be found from other studies of China's stock market, such as Eun and Huang (2007). Furthermore, Liu (2013) provides Figure 6 that depicts stock liquidity measured by the annual turnover of shares against the average share price of the stock during the year, which clearly has a negative pattern. This pattern is a consistent reiteration to our finding for China's negative effect of liquidity on the returns.

It is noticeable from the first row in the China Panel of Table 10, that without the control of the macroeconomic shocks, our estimation shows a positive relation for the pre-crisis and the during-crisis period. This finding is also reported by Narayan and Zheng (2011) for 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.

[INSERT TABLE 10 AND FIGURE 6 HERE]

5. Conclusions

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 in our opinion the four most representative stock markets in the world. Germany, the UK, the US and China, for our investigation across three time periods: pre-crisis, during-crisis and post-crisis period. The crises relates to the credit crunch financial turmoil of 2007.

Our empirical analysis begins with 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 with 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 literature 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 identified the accounting-link flaw of the classic Amihud momentum $R100_{it-1}$ in relation to the stock returns R_{it}, and therefore we refine $R100_{it-1}$ by removing the accounting link of the two variables for estimation. Finally, we consider the possible presence of the autocorrelation of $R100_{it-1}$ with R_{it} by using the instrumental $R100_{it-1}$ for estimation. The five augments provide the study with a methodological advantage for 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 a 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 on 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 very dominant negative pattern across the three time periods. Interestingly, the US as the largest stock market in the world, has inconclusive evidence regarding the association between 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 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. In this sense, we argue that the study of the liquidity relation to the returns has important implications for market efficiency.

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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

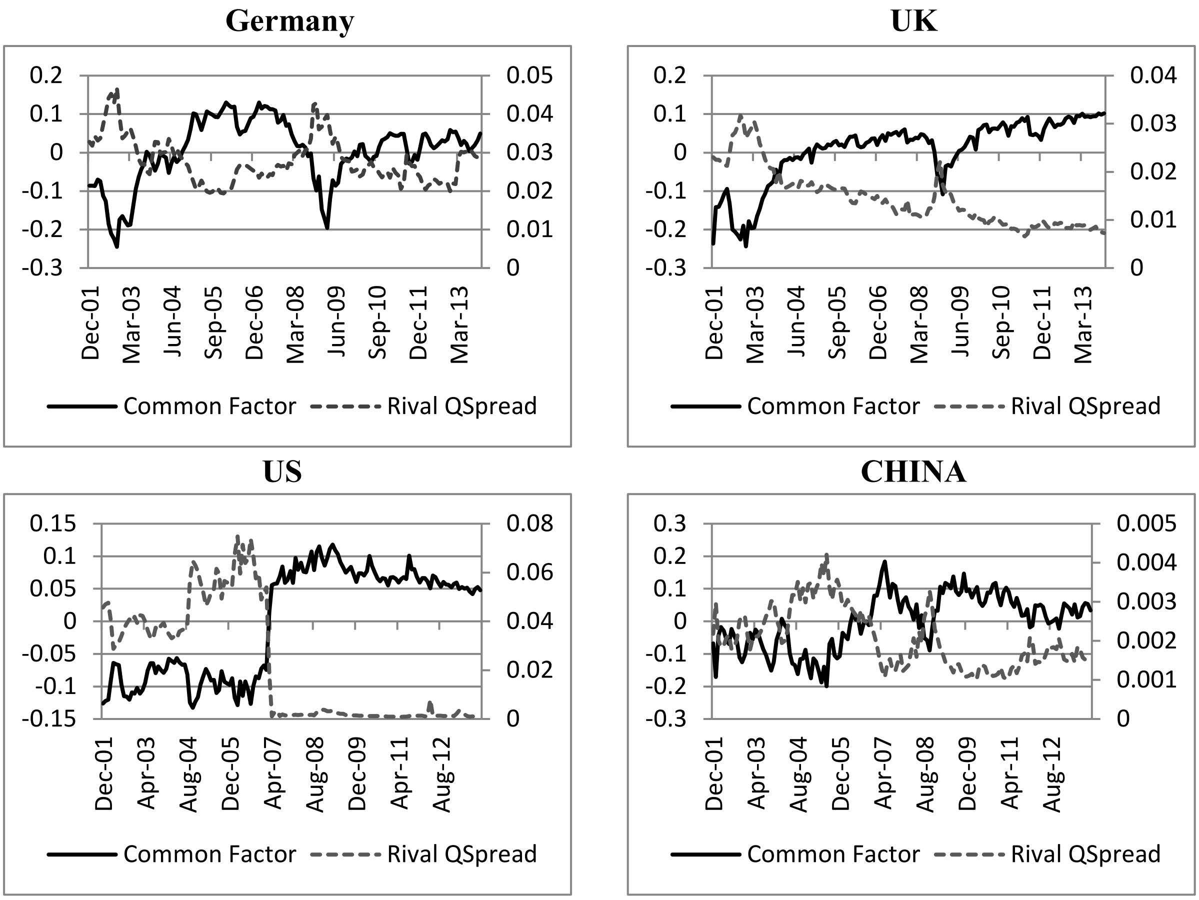

Figure 2 Scatter of Germany the returns vs market illiquidity 2010-13

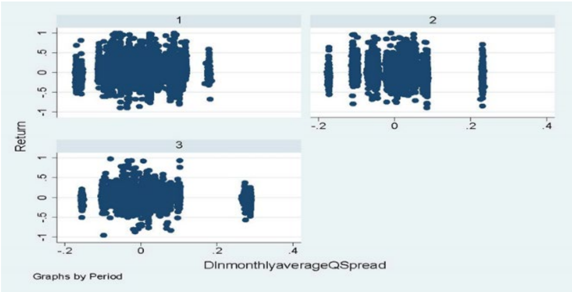

Table 2 The estimated effect of illiquidity on the returns across different samples of Germany

Estimation is made on the basis of equation (7.2) and we only report the effect of $\Delta\bar{L}^{M}_{jt-1}$ on R_{it} below.			
Germany	**Aggregate Observations**	**Without outliers**	**Small group of outliers**
2010-2013	-0.112**	-0.143**	-0.0298
observations	18,499	17,317	1,182

Figure 3 Scatter of the US returns vs market illiquidity

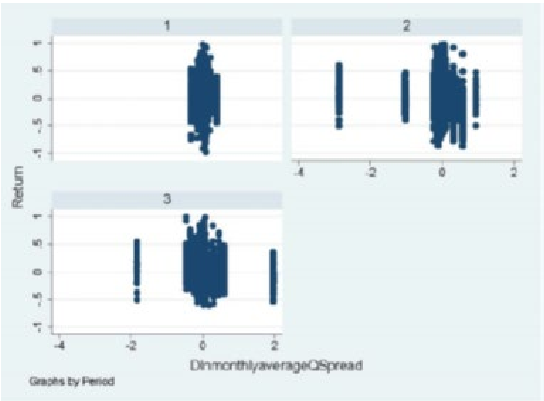

Table 3 The estimated effect of illiquidity on the returns across different samples in the US

Estimation is made on the basis of equation (7.2) and we only report the effect of $\Delta\bar{L}^{M}_{jt-1}$ on R_{it} below.			
US	**Aggregate Observations**	**Without outliers**	**Small group of outliers**
2007-2009	-0.0233**	-0.0665**	-0.0181**
observations	41,942	38,522	3,420
2010-2013	-0.0370**	-0.0216**	-0.0198**
observations	57,789	55,344	2,445

Figure 4 The monthly average stock price: UK, US, Germany and China 2002-2013

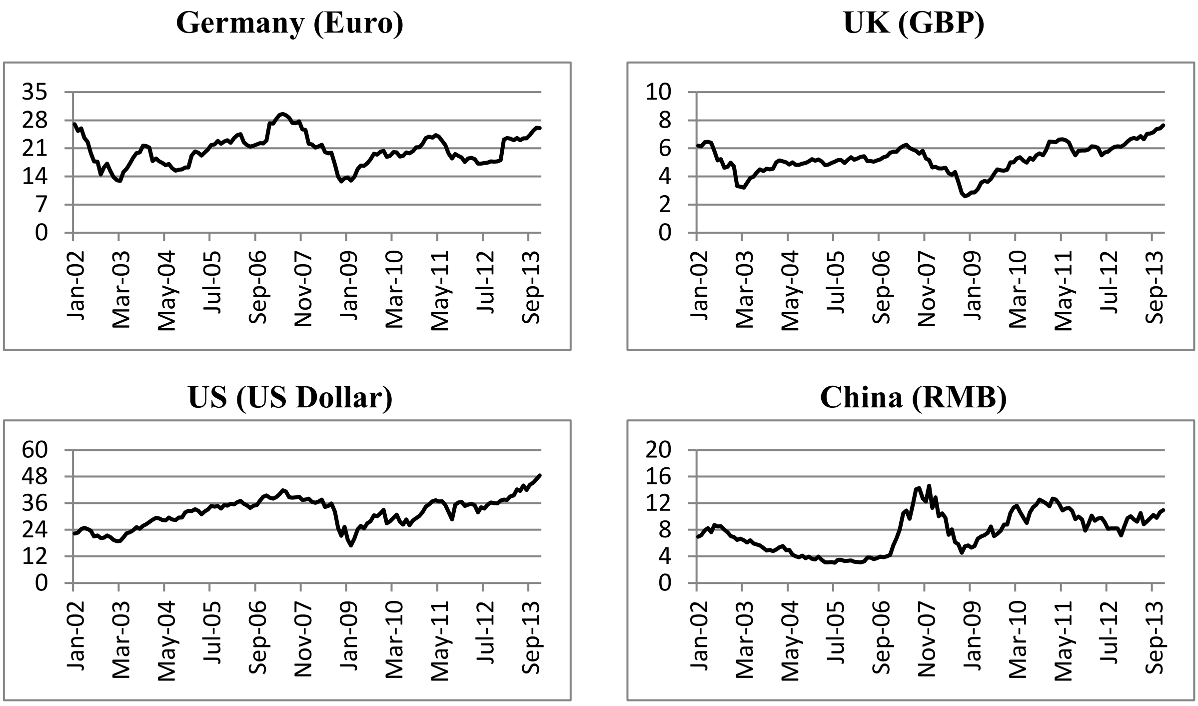

Figure 5 The monthly average stock returns: UK, US, Germany and China 2002-2013

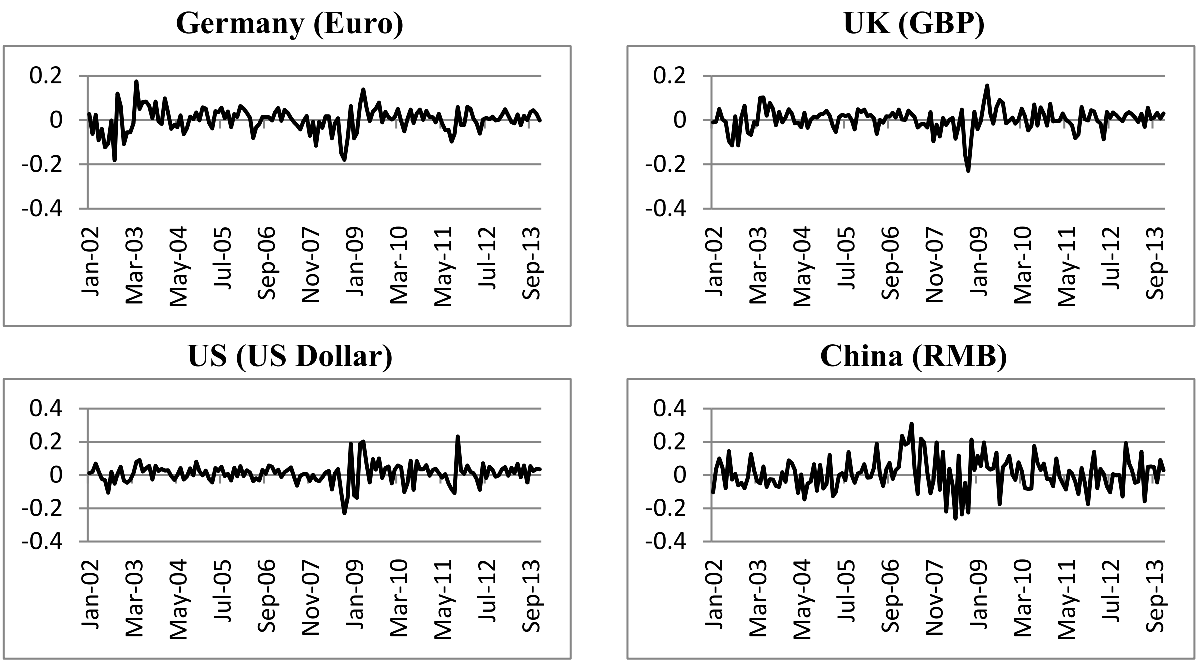

Table 4 Descriptive Statistics of Variables: UK, US, Germany and China

Variable	Germany (EUR)				UK (GBP)			
	N	Mean	P50	SD	N	Mean	P50	SD
Returns(R_{it})	59955	0.004	-0.001	0.135	59555	0.004	0.004	0.110
Mkt illiquidity	59955	0.028	0.022	0.022	59555	0.015	0.007	0.018
$R100_{it-1}$	59955	0.033	0.013	0.270	59555	0.037	0.031	0.218
$R265_{it-3}$	59955	0.077	0.011	0.572	59555	0.101	0.070	0.444
Volatility (V_{it-1})	59955	0.029	0.024	0.020	59555	0.020	0.017	0.013
Firm Size($*10^9$)	59955	1.430	0.112	4.130	59555	1.890	0.417	4.890
Variable	**US (USD)**				**China (RMB)**			
	N	**Mean**	**P50**	**SD**	**N**	**Mean**	**P50**	**SD**
Returns(R_{it})	165957	0.010	0.008	0.119	150750	0.008	0.000	0.137
Mkt illiquidity	165957	0.022	0.003	0.033	150750	0.002	0.002	0.001
$R100_{it-1}$	165957	0.053	0.041	0.243	150750	0.023	-0.016	0.258
$R265_{it-3}$	165957	0.113	0.065	0.518	150750	0.100	-0.054	0.585
Volatility (V_{it-1})	165957	0.024	0.020	0.017	150750	0.027	0.025	0.011
Firm Size($*10^9$)	165957	5.170	1.730	9.480	150750	4.670	2.680	6.190

Table 5 Correlation between Year Dummies and the Variables of Market Liquidity (Germany)

Pre-Crisis	**YR03**	**YR04**	**YR05**	**YR06**
Common factor (L^C_{t-1})	-0.634***	-0.372***	-0.068***	0.459***
First Difference CF (ΔL^C_{t-1})	-0.369***	0.272***	0.048***	0.108***
Rival Average ($\bar{L}^M_{jt-1}$)	0.656***	0.155***	0.211***	-0.551***
First Difference RA($\Delta \bar{L}^M_{jt-1}$)	0.284***	-0.230***	-0.050***	-0.205***
During-Crisis	**YR07**	**YR08**	**YR09**	
Common factor (L^C_{t-1})	0.753***	-0.058***	-0.763***	
First Difference CF (ΔL^C_{t-1})	0.101***	-0.251***	0.155***	
Rival Average ($\bar{L}^M_{jt-1}$)	-0.711***	0.256***	0.505***	
First Difference RA($\Delta \bar{L}^M_{jt-1}$)	0.003	0.297***	-0.317***	
Post-Crisis	**YR10**	**YR11**	**YR12**	**YR13**
Common factor (L^C_{t-1})	-0.485***	0.113***	0.108***	0.280***
First Difference CF (ΔL^C_{t-1})	0.065***	-0.114***	0.036***	0.008
Rival Average ($\bar{L}^M_{jt-1}$)	0.128***	0.039***	-0.579***	0.430***
First Difference RA($\Delta \bar{L}^M_{jt-1}$)	-0.051***	0.083***	-0.078***	0.051***

Table 6 Germany: The full estimation of market liquidity on stock returns over 3 periods

Germany	**Pre-Crisis**		**During-Crisis**		**Post-Crisis**	
Exclude January	**Stock Returns (R_{it})**		**Stock Returns (R_{it})**		**Stock Returns (R_{it})**	
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_{it-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)
$R100_{it-1}$	0.0124***	0.00876*	0.000423	0.000384	-0.00168	0.00267
	(2.7)	(1.9)	(0.06)	(0.05)	(-0.2)	(0.4)
$R260_{it-3}$	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_{it-}	-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***
$\widehat{R100_{it-1}}$: H	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. 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 equation (12). 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 $R100_{it-1}$ is used for estimation if the Hausman statistic ($\widehat{R100_{it-1}}$: H (χ^2)) is not significant in testing the presence of the autocorrelation of $R100_{it-1}$ to R_{it}. Otherwise, if it is significant, the instrumental $R100_{it-1}$ ($\widehat{R100_{it-1}}$) predicted by $R100_{it-2}$ 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:

$$R_{it} = \alpha + \lambda\Delta\bar{L}^{M}_{jt-1} + b_{11}LnS_{it-1} + b_{22}R100_{it-1} + b_{33}R260_{it-3} + b_{44}V_{it-1} + F_i + Y_T + \varepsilon_{it}$$

$$R_{it} = \alpha + \theta\Delta L^{C}_{t-1} + b_1 LnS_{it-1} + b_2 R100_{it-1} + b_3 R260_{it-3} + b_4 V_{it-1} + F_i + Y_T + \varepsilon_{it}$$

Table 7 The UK: The full estimation of market liquidity on stock returns over 3 periods

UK	Pre-Crisis		During-Crisis		Post-Crisis	
Exclude January	Stock Returns (R_{it})		Stock Returns (R_{it})		Stock Returns (R_{it})	
mkt illiquidity, λ	-0.0822***		-0.1000***		-0.0760***	
($\Delta \bar{L}_{jt-1}^{M}$)	(-6.5)		(-5.4)		(-6.2)	
mkt liquidity, θ		0.0956***		0.0705		0.0867
(ΔL_{t-1}^{C})		(3.3)		(0.9)		(1.4)
Size (LnS_{it-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)
$R100_{it-1}$	0.00945*	0.00261	0.0120	0.0149**	-0.0223***	-0.0181***
	(1.7)	(0.3)	(1.6)	(2.0)	(-3.6)	(-3.0)
$R260_{it-3}$	-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_{it-}	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***
$\widehat{R100_{it-1}}$: H	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 6.

Table 8 The US: The full estimation of market liquidity on stock returns over 3 periods

US	Pre-Crisis		During-Crisis		Post-Crisis	
Exclude January	Stock Returns (R_{it})		Stock Returns (R_{it})		Stock Returns (R_{it})	
mkt illiquidity, λ	0.0235***		-0.0751***		-0.0226***	
($\Delta \bar{L}_{jt-1}^{M}$)	(7.4)		(-25.1)		(-10.2)	
mkt liquidity, θ		-0.0728***		-1.176***		-2.867***
(ΔL_{t-1}^{C})		(-3.3)		(-24.5)		(-49.4)
Size (LnS_{it-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)
$R100_{it-1}$	-0.00697	0.00388	0.0798***	0.0720***	-0.00914*	0.0273***
	(-1.4)	(1.3)	(14.2)	(13.0)	(-1.7)	(5.1)
$R260_{it-3}$	-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_{it-}	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***
$\widehat{R100_{it-1}}$: H	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 6.

Table 9 China: The full estimation of market liquidity on stock returns over 3 periods

China	Pre-Crisis		During-Crisis		Post-Crisis	
Exclude January	Stock Returns (R_{it})		Stock Returns (R_{it})		Stock Returns (R_{it})	
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_{it-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)
$R100_{it-1}$	0.0338***	0.0356***	0.151***	0.157***	0.00833	0.00471
	(6.1)	(6.4)	(21.4)	(21.7)	(1.4)	(0.8)
$R260_{it-3}$	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_{it-}	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***
$R\widehat{100}_{it-1}$: H	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 6.

Table 10 How market liquidity affects the returns? a summary report 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						
Without control of macro shocks	-0.0731***	0.125***	-0.0627***	0.0674***	0.0783***	-0.384***
	25,448	*25,448*	*16,712*	*16,712*	*17,795*	*17,795*
Control of macro shocks by yr dummy	0.00171	-0.107***	0.0216*	-0.0560*	0.0844***	-0.447***
	25,448	*25,448*	*16,712*	*16,712*	*17,795*	*17,795*
Control macro shock and multicollinearity	-0.0252	0.358***	-0.0431*	0.204***	-0.143***	-0.100
	24,278	*24,278*	*16,222*	*16,222*	*17,317*	*17,317*
Control macro shock and multicollinearity and January effect	-0.0696***	0.414***	-0.0859***	0.155***	-0.139***	-0.0986
	23,113	*23,113*	*15,346*	*15,346*	*15,862*	*15,862*
Control macro shock and multicol. and Jan eff and instrument $R100_{it-1}$	-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						
Without control of macro shocks	-0.0346***	0.137***	0.0327***	-0.274***	0.0541***	0.0123
	26,515	*26,515*	*15,194*	*15,194*	*17,846*	*17,846*
Control of macro shocks by yr dummy	0.0615***	-0.0315	-0.00097	-0.190***	0.0727***	-0.370***
	26,515	*26,515*	*15,194*	*15,194*	*17,846*	*17,846*
Control macro shock and multicollinearity	0.00036	0.178***	-0.0951***	0.0609	-0.0509***	0.155***
	25,251	*25,251*	*14,753*	*14,753*	*17,259*	*17,259*
Control macro shock and multicollinearity and January effect	-0.0822***	0.0758**	-0.1000***	0.0705	-0.0760***	0.0867
	23,781	*23,781*	*14,301*	*14,301*	*15,924*	*15,924*
Control macro shock and multicol. and Jan eff and instrument $R100_{it-1}$	-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						
Without control of macro shocks	0.0599***	-0.291***	0.00563***	-0.196***	0.0271***	-1.467***
	70,016	*70,016*	*39,478*	*39,478*	*56,463*	*56,463*
Control of macro shocks by yr dummy	0.0735***	-0.389***	-0.00065	-0.0586***	0.0158***	-1.173***
	70,016	*70,016*	*39,478*	*39,478*	*56,463*	*56,463*
Control macro shock and multicollinearity	0.0172***	-0.0474**	-0.0665***	-0.824***	-0.0216***	-2.436***
	67,196	*67,196*	*38,522*	*38,522*	*55,344*	*55,344*
Control macro shock and multicollinearity	0.0252***	-0.0728***	-0.0699***	-1.194***	-0.0230***	-2.790***
	62,803	*62,803*	*35,214*	*35,214*	*50,700*	*50,700*

and January effect						
Control macro shock and multicol. and Jan eff and instrumental $R100_{it-1}$	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						
Without control of macro shocks	-0.0327***	0.135***	-0.0602***	0.574***	0.0926***	-0.453***
	49,539	*49,539*	*34,013*	*34,013*	*67,198*	*67,198*
Control of macro shocks by yr dummy	0.0204***	-0.0667***	0.0646***	-0.249***	0.183***	-0.929***
	49,539	*49,539*	*34,013*	*34,013*	*67,198*	*67,198*
Control macro shock and multicollinearity	0.0328***	-0.0541***	0.273***	-0.654***	0.0914***	-0.399***
	46,968	*46,968*	*32,621*	*32,621*	*64,790*	*64,790*
Control macro shock and multicollinearity and January effect	0.0890***	-0.238***	0.308***	-0.684***	0.107***	-0.702***
	43,766	*43,766*	*30,272*	*30,272*	*61,174*	*61,174*
Control macro shock and multicol. and Jan eff and instrumental $R100_{it-1}$	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: 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 their corresponding observations used for the estimation. It has five rows representing five different methods of investigation for each market. The fifth row of 'Control of macro shocks and multicol and jan eff and instrumental $R100_{it-1}$', means we have controlled the macro shocks, multicollinearity effect and the January effect in estimation together with use of the instrumental variable $R100_{it-1}$ for estimation.

Figure 6 China: stock price versus its stock liquidity 1999 to 2010

Appendix I Full Estimation of the Effect of Market Liquidity on Stock Returns

$$R_{it} = \theta_{20} + \theta_{21}L^{M}_{t-1} + \theta_{22}LnSIZE_{it-1} + \theta_{23}R100_{it-1} + \theta_{24}R265_{it-3} + \theta_{25}Volatility_{it-1} + F_i + YeDum_T + \varepsilon_{it}$$

$$R_{it} = \lambda_{20} + \lambda_{21}\bar{L}^{M}_{jt-1} + \lambda_{22}LnSIZE_{it-1} + \lambda_{23}R100_{it-1} + \lambda_{24}R265_{it-3} + \lambda_{25}Volatility_{it-1} + F_i + YeDum_T + \varepsilon_{it}$$

Germany	Pre-Crisis		During-Crisis		Post-Crisis	
	Stock Returns (R_{it})		Stock Returns (R_{it})		Stock Returns (R_{it})	
mkt illiquidity, λ	0.00171		0.0216*		0.0844***	
($\bar{L}^{M}_{jt-1}$)	(0.20)		(1.78)		(9.46)	
mkt liquidity, θ		-0.107***		-0.0560*		-0.447***
(L^{C}_{t-1})		(-4.03)		(-1.88)		(-10.83)
Size (LnS_{it-1})	-0.0660***	-0.0643***	-0.0754***	-0.0754***	-0.0466***	-0.0445***
	(-14.52)	(-14.39)	(-11.80)	(-11.86)	(-10.62)	(-10.43)
$R100_{it-1}$	0.0176***	0.0214***	0.00381	0.00388	-0.00197	0.00430
	(4.01)	(4.84)	(0.60)	(0.61)	(-0.31)	(0.68)
$R265_{it-3}$	0.00563***	0.00591***	-0.00796**	-0.00779*	0.00374	0.00466**
	(2.96)	(3.13)	(-1.98)	(-1.92)	(1.60)	(1.99)
Volatility (V_{it-1})	-0.0541	-0.0954	-0.209*	-0.203*	-0.366***	-0.390***
	(-0.63)	(-1.11)	(-1.90)	(-1.85)	(-2.75)	(-2.92)
Constant	1.281***	1.251***	1.501***	1.423***	1.217***	0.886***
	(14.99)	(14.73)	(13.48)	(11.96)	(12.99)	(10.85)
Obs.	25,448	25,448	16,712	16,712	17,795	17,795
R^2	0.099	0.100	0.132	0.132	0.081	0.084
Adj.R^2	0.0743	0.0752	0.0941	0.0941	0.0528	0.0556
F test	82.11***	88.29***	130.4***	129.7***	47.08***	57.95***
UK	**Pre-Crisis**		**During-Crisis**		**Post-Crisis**	
	Stock Returns (R_{it})		**Stock Returns (R_{it})**		**Stock Returns (R_{it})**	
mkt illiquidity, λ	0.0615***		-0.000974		0.0727***	
($\bar{L}^{M}_{jt-1}$)	(8.70)		(-0.10)		(8.12)	
mkt liquidity, θ		-0.0315		-0.190***		-0.370***
(L^{C}_{t-1})		(-1.53)		(-3.27)		(-7.58)
Size (LnS_{it-1})	-0.0556***	-0.0588***	-0.0725***	-0.0689***	-0.0569***	-0.0579***
	(-10.98)	(-11.23)	(-9.99)	(-9.69)	(-12.03)	(-12.19)
$R100_{it-1}$	0.0234***	0.0178***	0.0153**	0.0166**	-0.0174***	-0.0165***
	(4.68)	(3.51)	(2.05)	(2.28)	(-2.78)	(-2.62)
$R265_{it-3}$	0.00410*	0.00321	-0.00774**	-0.00610*	0.00732***	0.00734***
	(1.71)	(1.32)	(-2.14)	(-1.78)	(2.60)	(2.59)
Volatility (V_{it-1})	0.0200	0.0774	-0.346*	-0.423**	-0.0424	-0.0662
	(0.21)	(0.81)	(-1.85)	(-2.25)	(-0.34)	(-0.52)
Constant	1.376***	1.181***	1.461***	1.398***	1.533***	1.242***
	(15.10)	(11.37)	(10.19)	(9.85)	(15.47)	(12.78)
Obs.	26,515	26,515	15,194	15,194	17,846	17,846
R^2	0.089	0.086	0.127	0.128	0.082	0.081
Adj.R^2	0.0632	0.0602	0.0867	0.0876	0.0532	0.0526
F test	83.29***	64.23***	117.1***	120.7***	54.80***	54.23***

US	Pre-Crisis		During-Crisis		Post-Crisis	
	Stock Returns (R_{it})		Stock Returns (R_{it})		Stock Returns (R_{it})	
mkt illiquidity, λ	0.0735***		-0.00065		0.0158***	
($\bar{L}^{M}_{jt-1}$)	(32.20)		(-1.05)		(10.17)	
mkt liquidity, θ		-0.389***		-0.0586***		-1.173***
(L^{C}_{t-1})		(-21.20)		(-3.49)		(-20.52)
Size (LnS_{it-1})	-0.0504***	-0.0488***	-0.144***	-0.144***	-0.0686***	-0.0697***
	(-21.01)	(-20.70)	(-26.69)	(-26.66)	(-21.80)	(-21.47)
$R100_{it-1}$	0.00374	0.00569**	0.0322***	0.0319***	-0.0256***	-0.0331***
	(1.30)	(1.96)	(9.29)	(9.17)	(-7.12)	(-8.95)
$R265_{it-3}$	0.00345**	0.00246*	0.0135***	0.0135***	0.00165	0.00166
	(2.47)	(1.79)	(5.45)	(5.49)	(1.51)	(1.51)
Volatility (V_{it-1})	0.216***	0.171**	-0.889***	-0.858***	-0.414***	0.120*
	(3.17)	(2.50)	(-12.62)	(-11.53)	(-6.48)	(1.69)
Constant	1.296***	1.021***	3.098***	3.090***	1.622***	1.593***
	(24.85)	(20.12)	(27.14)	(27.03)	(24.46)	(22.52)
Obs.	70,016	70,016	39,478	39,478	56,463	56,463
R^2	0.073	0.067	0.117	0.118	0.066	0.072
Adj.R^2	0.0529	0.0468	0.0851	0.0853	0.0408	0.0467
F test	227.8***	172.0***	346.5***	351.1***	130.9***	132.4***
China	**Pre-Crisis**		**During-Crisis**		**Post-Crisis**	
	Stock Returns (R_{it})		**Stock Returns (R_{it})**		**Stock Returns (R_{it})**	
mkt illiquidity, λ	0.0204***		0.0646***		0.183***	
($\bar{L}^{M}_{jt-1}$)	(5.66)		(9.64)		(46.50)	
mkt liquidity, θ		-0.0667***		-0.249***		-0.929***
(L^{C}_{t-1})		(-5.37)		(-9.09)		(-48.54)
Size (LnS_{it-1})	-0.0472***	-0.0483***	-0.202***	-0.214***	-0.0819***	-0.0802***
	(-14.95)	(-15.64)	(-32.88)	(-38.74)	(-22.92)	(-22.59)
$R100_{it-1}$	-0.0454***	-0.0442***	0.0145***	0.0172***	-0.0503***	-0.0526***
	(-11.90)	(-11.14)	(3.60)	(4.18)	(-14.87)	(-15.69)
$R265_{it-3}$	0.00497	0.00544*	0.0530***	0.0496***	0.0238***	0.0183***
	(1.61)	(1.77)	(25.74)	(24.17)	(15.17)	(11.58)
Volatility (V_{it-1})	0.627***	0.673***	0.919***	1.122***	1.269***	1.463***
	(8.96)	(9.89)	(10.11)	(12.98)	(19.12)	(22.29)
Constant	1.130***	1.031***	4.861***	4.719***	2.974***	1.789***
	(18.09)	(15.91)	(46.51)	(40.00)	(41.44)	(23.09)
Obs.	49,539	49,539	34,013	34,013	67,198	67,198
R^2	0.068	0.068	0.277	0.276	0.143	0.143
Adj.R^2	0.0450	0.0450	0.249	0.248	0.115	0.115
F test	294.7***	275.1***	1787***	1785***	1314***	1425***

Appendix II Full Estimation of the Effect of Market Liquidity on Stock Returns [based on Model (7.1) and (7.2) without instrument of the first momentum]

$$R_{it} = \theta_{30} + \theta_{31}\Delta L^{M}_{t-1} + \theta_{32}LnSIZE_{it-1} + \theta_{33}R100_{it-1} + \theta_{34}R265_{it-3} + \theta_{35}Volatility_{it-1} + F_i + YeDum_T + \varepsilon_{it}$$
$$R_{it} = \lambda_{30} + \lambda_{31}\Delta \bar{L}^{M}_{jt-1} + \lambda_{32}LnSIZE_{it-1} + \lambda_{33}R100_{it-1} + \lambda_{34}R265_{it-3} + \lambda_{35}Volatility_{it-1} + F_i + YeDum_T + \varepsilon_{it}$$

Germany Exl. Jan	Pre-Crisis		During-Crisis		Post-Crisis	
	Stock Returns (R_{it})		Stock Returns (R_{it})		Stock Returns (R_{it})	
mkt illiquidity, λ	-0.0696***		-0.0859***		-0.139***	
($\Delta \bar{L}^{M}_{jt-1}$)	(-4.003)		(-3.54)		(-7.17)	
mkt liquidity, θ		0.414***		0.155***		-0.0986
(ΔL^{C}_{t-1})		(9.52)		(3.43)		(-1.53)
Size (LnS_{it-1})	-0.0659***	-0.0667***	-0.0772***	-0.0776***	-0.0451***	-0.0451***
	(-13.74)	(-13.74)	(-12.03)	(-12.00)	(-9.85)	(-9.94)
$R100_{it-1}$	0.0124***	0.00876*	0.000423	0.000384	-0.00168	0.00267
	(2.70)	(1.88)	(0.063)	(0.058)	(-0.26)	(0.40)
$R265_{it-3}$	0.00454**	0.00549***	-0.00387	-0.00448	0.00515**	0.00490**
	(2.17)	(2.60)	(-0.88)	(-1.03)	(2.07)	(2.00)
Volatility (V_{it-1})	-0.0209	-0.00856	-0.0614	-0.0807	-0.204	-0.260*
	(-0.23)	(-0.10)	(-0.49)	(-0.64)	(-1.43)	(-1.81)
Constant	1.271***	1.285***	1.455***	1.465***	0.878***	0.877***
	(13.78)	(13.77)	(12.16)	(12.14)	(9.94)	(10.04)
Obs.	23,113	23,113	15,346	15,346	15,862	15,862
R^2	0.111	0.113	0.126	0.126	0.089	0.086
Adj.R^2	0.0839	0.0865	0.0847	0.0847	0.0581	0.0546
F test	88.79***	90.72***	98.29***	95.60***	46.27***	41.42***

UK Exl. Jan	Pre-Crisis		During-Crisis		Post-Crisis	
	Stock Returns (R_{it})		Stock Returns (R_{it})		Stock Returns (R_{it})	
mkt illiquidity, λ	-0.0822***		-0.1000***		-0.0760***	
($\Delta \bar{L}^{M}_{jt-1}$)	(-6.46)		(-5.43)		(-6.21)	
mkt liquidity, θ		0.0758**		0.0705		0.0867
(ΔL^{C}_{t-1})		(2.56)		(0.93)		(1.43)
Size (LnS_{it-1})	-0.0585***	-0.0582***	-0.0796***	-0.0787***	-0.0589***	-0.0591***
	(-13.56)	(-13.59)	(-10.69)	(-10.53)	(-11.99)	(-12.09)
$R100_{it-1}$	0.00945*	0.0140**	0.0120	0.0149**	-0.0223***	-0.0181***
	(1.66)	(2.57)	(1.57)	(2.01)	(-3.56)	(-2.99)
$R265_{it-3}$	-0.00110	-0.000905	-0.00651*	-0.00621	0.00997***	0.0103***
	(-0.42)	(-0.34)	(-1.70)	(-1.64)	(3.24)	(3.33)
Volatility (V_{it-1})	0.228**	0.203*	-0.394**	-0.476***	0.0976	0.0554
	(2.11)	(1.89)	(-2.14)	(-2.64)	(0.71)	(0.40)
Constant	1.170***	1.164***	1.602***	1.590***	1.221***	1.229***
	(13.63)	(13.67)	(10.80)	(10.67)	(12.08)	(12.19)
Obs.	23,781	23,781	14,301	14,301	15,924	15,924
R^2	0.097	0.095	0.132	0.130	0.081	0.079
Adj.R^2	0.0683	0.0668	0.0897	0.0877	0.0497	0.0474
F test	77.48***	78.19***	108.8***	110.0***	39.45***	38.82***

US Exl. Jan	Pre-Crisis Stock Returns (R_{it})		During-Crisis Stock Returns (R_{it})		Post-Crisis Stock Returns (R_{it})	
mkt illiquidity, λ	0.0252***		-0.0699***		-0.0230***	
$(\Delta \bar{L}^{M}_{jt-1})$	(8.00)		(-23.95)		(-10.28)	
mkt liquidity, θ		-0.0728***		-1.194***		-2.790***
(ΔL^{C}_{t-1})		(-3.26)		(-24.44)		(-49.60)
Size (LnS_{it-1})	-0.0494***	-0.0494***	-0.142***	-0.139***	-0.0731***	-0.0697***
	(-19.54)	(-19.51)	(-25.95)	(-25.74)	(-22.09)	(-21.76)
$R100_{it-1}$	0.00498	0.00388	0.00606	0.00293	-0.0282***	-0.0121***
	(1.64)	(1.27)	(1.54)	(0.74)	(-7.26)	(-3.20)
$R265_{it-3}$	-0.00139	-0.00144	0.0225***	0.0170***	0.00299**	0.00662***
	(-0.77)	(-0.79)	(9.05)	(6.80)	(2.56)	(5.29)
Volatility (V_{it-1})	0.290***	0.296***	-0.427***	-0.463***	-0.487***	-0.0218
	(4.12)	(4.19)	(-5.25)	(-5.72)	(-7.26)	(-0.34)
Constant	1.069***	1.068***	3.043***	2.999***	1.615***	1.530***
	(19.68)	(19.66)	(26.13)	(25.97)	(22.56)	(22.09)
Obs.	62,803	62,803	35,214	35,214	50,700	50,700
R^2	0.071	0.070	0.151	0.155	0.069	0.127
Adj.R^2	0.0483	0.0476	0.116	0.120	0.0409	0.101
F test	152.0***	141.4***	458.2***	486.2***	109.5***	393.2***

China Exl. Jan	Pre-Crisis Stock Returns (R_{it})		During-Crisis Stock Returns (R_{it})		Post-Crisis Stock Returns (R_{it})	
mkt illiquidity, λ	0.0890***		0.308***		0.107***	
$(\Delta \bar{L}^{M}_{jt-1})$	(22.49)		(60.08)		(27.96)	
mkt liquidity, θ		-0.238***		-0.684***		-0.702***
(ΔL^{C}_{t-1})		(-19.11)		(-39.14)		(-38.27)
Size (LnS_{it-1})	-0.0553***	-0.0559***	-0.263***	-0.256***	-0.0954***	-0.0932***
	(-18.04)	(-18.05)	(-44.01)	(-43.57)	(-22.93)	(-22.80)
$R100_{it-1}$	-0.0293***	-0.0343***	0.0676***	0.0416***	-0.0777***	-0.0762***
	(-8.31)	(-9.82)	(13.49)	(8.61)	(-21.22)	(-20.97)
$R265_{it-3}$	0.0236***	0.0227***	0.0568***	0.0569***	0.0317***	0.0286***
	(7.79)	(7.43)	(22.84)	(23.12)	(16.07)	(14.66)
Volatility (V_{it-1})	0.775***	0.805***	-0.0809	1.095***	1.769***	1.795***
	(11.27)	(11.61)	(-0.75)	(10.58)	(25.67)	(26.16)
Constant	1.173***	1.185***	5.812***	5.624***	2.078***	2.030***
	(18.23)	(18.24)	(44.81)	(44.06)	(22.81)	(22.66)
Obs.	43,766	43,766	30,272	30,272	61,174	61,174
R^2	0.082	0.081	0.299	0.273	0.125	0.131
Adj.R^2	0.0566	0.0561	0.269	0.242	0.0942	0.100
F test	355.8***	308.0***	1768***	1304***	695.9***	801.8***