Emerging Markets Review 38 (2019) 159–181

Contents lists available at ScienceDirect

Emerging Markets Review

journal homepage: www.elsevier.com/locate/emr

Flight-to-liquidity: Evidence from China's stock market

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ARTICLE INFO

Keywords:
Stock illiquidity
Stock returns
High frequency bid-ask spreads
Financial anomalies

JEL classification:
G10
G11
F39
G12
G14

ABSTRACT

In an order-driven and strictly regulated stock market, illiquidity risks' effects on asset pricing should be highlighted, particularly in such extreme market conditions as those in China. This paper utilizes panel data from China's stock market in an attempt to answer whether the illiquidity risk in various dimensions—including price impacts, the transaction speed, trading volume, transaction costs, and asymmetric information—can explain stock returns. We find that almost all dimensions of stock illiquidity are positively associated with excess stock returns. More importantly, smaller, less-liquid stocks suffer more liquidity costs, providing a strong evidence for “flight-to-liquidity.” Additionally, the transaction costs and asymmetric information, denoted by bid-ask spreads, robustly account for these illiquidity effects on stock pricing and differ from the findings in the U.S. market. We also find that the “flight-to-liquidity” can partially explain the idiosyncratic volatility puzzle, investors' gambling, and herding psychologies. This study provides substantial policy implications in regulation and portfolio management for emerging markets.

1. Introduction

Liquidity is risky and varies over time both for individual stocks and the market as a whole. The liquidity risk has been extensively studied in market-maker-driven stock markets with developed investor structure and trading rules (Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Chordia et al., 2004; Acharya and Pedersen, 2005). However, the liquidity risk of some emerging stock markets and its effects may be different from that of developed markets due to their order-driven market structures, dominant role of private investors, and strict trading rules, such as China's stock market. In such stock markets, asymmetric information and transaction cost are more serious. Thus, one may ask whether the individual illiquidity risk (or liquidity risk) influences stock returns, and if so, whether the illiquidity effects on stock returns vary across time horizons (daily, monthly, and yearly) as well as across different dimensions of illiquidity. More importantly, one may also question whether the relationship between illiquidity and stock returns is attributed to the level of liquidity (or size effects), which is an evidence for “flight-to-liquidity.” Finally, it can also be posited whether the “flight-to-liquidity” can explain some financial anomalies, such as the idiosyncratic volatility puzzle and gambling (idiosyncratic skewness) and herding (momentum) effects. This paper answers these questions by studying the effects of illiquidity on stock returns with panel data across various time horizons and dimensions of illiquidity. The answers to these questions will not only provide further understanding as to whether these useful factors, evident in mature markets, relate to fundamentals, but also reveal additional important factors in pricing stocks in emerging markets.

As illiquidity has many dimensions and includes substantial amounts of trading information, any single illiquidity measurement

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https://doi.org/10.1016/j.ememar.2019.01.001
Received 10 August 2017; Received in revised form 2 January 2019; Accepted 15 January 2019
Available online 24 January 2019
1566-0141/

measures illiquidity with errors. Most studies employ low frequency, indirect illiquidity measures in their empirical analyses, while less concerned with high-frequency, direct illiquidity measures. In actuality, finer and better measures of illiquidity exist, such as bid-ask spreads. These measures are generally based on the microstructure data currently available in China's stock market, and the data from China's stock market covers a longer length of time. Therefore, the present paper adopts different proxies of illiquidity measures—including a set of direct measures calculated by extra high-frequency data and other indirect measures—to examine the association between stock illiquidity and expected returns based on China's experience.

Our empirical analysis relies on two data sources: the China Security Market Trade and Quote Research Database (CSMAR) and the RESSET database. The empirical specification primarily refers to works by Amihud (2002) and Liu (2006), but studies individual stock illiquidity rather than the market average illiquidity. The panel data allows us to control for stock fixed-effects in our estimations, which mitigates problems with endogeneity. Our baseline results demonstrate that the stock illiquidity in most dimensions positively affects stock returns, and these effects are weaker for daily and annual data compared to the monthly data. We then consider the size's effects on the relationship between illiquidity and stock returns to discover that the smaller firms' stocks, or less liquid stocks, respond more to changes in illiquidity, including expected and unexpected illiquidity. This finding provides evidence for the “flight-to-liquidity” phenomenon (Amihud, 2002), which was first discovered in China's stock market. Additionally, high-frequency bid-ask spreads play a more robust role in analyzing the relationship between stock illiquidity and excess returns, suggesting the importance of an illiquidity measure reflecting transaction costs and asymmetric information. This also provides evidence for the theoretical model of asset pricing with liquidity risk.[1] This finding indicates that in an order-driven market structure, a majority of private investors and price impacts are a source of liquidity risk in China's stock market. After further controlling for the market risk, the model is extended to act as a liquidity-augmented capital asset-pricing model with size effects,[2] and the empirical results are consistent with previous findings.

Our study further discusses whether the “flight-to-liquidity” can explain some stock market anomalies. Previous studies have documented the existence of an idiosyncratic volatility puzzle (Ang et al., 2009; Long et al., 2018), idiosyncratic skewness factor (Boyer et al., 2007, 2010; Cao, 2015), and momentum (Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Lu and Zhou, 2007), and have attempted to deduce an underlying mechanism among these pricing factors. Our work also consistently discovers these apparent anomalies, and provides a new mechanism to explain these anomalies by using evidence of the “flight-to-liquidity.” We find that not only did liquidity and size independently impact stock returns, but their interactions are also evidence that the “flight-to-liquidity” can partially explain these financial anomalies. This finding contradicts a case in the U.S. stock market, in which size and liquidity could not explain the idiosyncratic volatility puzzle (Ang et al., 2006).

This paper is the first to our knowledge to jointly test the cross-sectional and time-series effects of stock illiquidity based on data from China's stock market and examine their underlying mechanism. Literature includes four main strands of related literature: The first, which includes extensive research, studies the cross-sectional effects of stock illiquidity on stock returns. For instance, Amihud and Mendelson (1986) and Eleswarapu (1997) found that quoted bid-ask spreads had significant, positive effects on stock returns. Brennan and Subrahmanyam (1996) measured stock illiquidity by price impacts to find that this positively affects stock returns based on the high-frequency data from transactions and quotes. Chalmers and Kadlec (1998) regarded the amortized effective spread as a measure of liquidity, and discovered that illiquidity positively affects stock returns. Easley et al. (2002) introduced a new measure of microstructure risk that reflects asymmetric information between traders. The authors suggested that the probability of information-based trading has a positive, significant effect on stock returns. Amihud (2002) also discovered cross-sectional, positive return illiquidity. Bekaert et al. (2007) examined the impact of liquidity on expected returns in emerging markets to reveal that local market liquidity is an important driver of expected returns.

The second strand of literature examines the time-series effects of market-wide changes in stock illiquidity on stock returns. For example, Amihud (2002) tested the illiquidity effects from the cross-sectional and time-series perspectives, respectively, to find that the expected stock returns for the current period are an increasing function of the expected illiquidity in that period, which is based on the prior period's illiquidity. Further, an unanticipated increase in the current period's illiquidity decreases stock prices in that period, generating a negative return-unexpected illiquidity relationship. Jones (2002) suggested that the transaction cost, a proxy for illiquidity, predicts stock returns one year or more ahead, while high spreads predict high stock returns.

The third strand of study relates to the liquidity-adjusted asset-pricing model. Zhang et al.'s (2009) empirical test on the floating-adjusted-return model demonstrated that systematic liquidity risk is priced with a premium annually, and the size and book-to-market equity help explain the cross-sectional variation in the Chinese market's stock returns. Narayan and Zheng (2010) studied market liquidity risk factors' roles in determining cross-sectional stock returns in a model that included financial market anomalies for an order-driven market. Yang (2015) used cross-sectional data to investigate how the non-tradable share reform affected the correlations between liquidity and stock returns.

The last strand of research discusses some stock market anomalies, such as the idiosyncratic volatility puzzle (Ang et al., 2009; Long et al., 2018), idiosyncratic skewness factor (Boyer et al., 2007, 2010; Cao, 2015), and momentum factor (Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Lu and Zhou, 2007). This paper attempts to explain those frequent financial anomalies from the “flight-to-liquidity” perspective.

This study primarily differs from previous research in the following four aspects: First, as far as we know, our study is the first to

[1] Detailed information on the theoretical model of asset pricing with liquidity risk is shown in Acharya and Pedersen's (2005) work, specifically, Section 2.4, Proposition 3.

[2] The liquidity-augmented capital asset-pricing model is similar to the two-factor model developed by Liu (2006).

investigate the relationship between illiquidity and stock returns by using panel data in daily, monthly, and yearly horizons. Second, we introduce various dimensions of illiquidity measures rather than a single measure; specifically, we take the high frequency bid-ask spreads as a proxy of illiquidity to reflect trading costs and information asymmetry, which robustly supports the illiquidity effects across time horizons. This suggests that a special market and investor structure can induce different illiquidity effects. Third, this paper's empirical models are developed from works by Amihud (2002) and Liu (2006) by adding size effects to explain the "flight-to-liquidity" phenomenon, and we find that this phenomenon is robust even after controlling for the market risk premium. It distinguishes our findings on liquidity effects from other literature regarding China's stock market (Narayan and Zheng, 2010; Zhang et al., 2013). Finally, our study also provides evidence that "flight-to-liquidity" acts as an independent pricing factor and can partially explain some financial anomalies, such as the idiosyncratic volatility puzzle, idiosyncratic skewness, and stock momentum. This is the first paper to highlight the independent role of "flight-to-liquidity" in asset pricing, which is used to explain these anomalies.

The remainder of the paper is organized as follows. Section 2 provides an overview of the institutional backgrounds and structure of China's stock market. Section 3 details the methodology, including the hypothesis development and an empirical modeling strategy. Section 4 primarily describes the data source and illiquidity measures. Section 5 reports the results, and Section 6 discusses some extensions. Section 7 concludes.

2. Background

Similar to most emerging stock markets, China's stock market suffers from unsatisfactory corporate governance, dubious accounting practices, market manipulation, and insider trading. However, China's stock market also has several unique characteristics. This section mainly describes five noteworthy, typical scenarios in China's stock market.

First, China's stock market is an order-driven system and lacks market makers. Each quote order is handled by a computer to ensure the market trade's continuity. Under this circumstance, the bid-ask spread is not the real spread provided by the market makers, but the difference between the lowest bid and highest quote; thus, these orders are effectively those without settlement. The buy-side or sell-side flow in this system promotes market and price formation. In other words, the price-formation process and risk factors might differ for Chinese equities. Second, more than two-thirds of the total market capitalization in 2000 was owned by the state. These state-owned shares cannot be traded on exchanges due to their ownership structure, but they were allowed to be traded in the market after such 2004 and 2005 reforms as the non-tradable share reform implemented by the China Securities Regulatory Commission (CSRC); the stockholder's role is transformed into that of a legal party. The policy transformations induce the management of market value by such legal parties, and to some extent, this improves market liquidity and creates uniform market pricing procedures. However, the government still highlights the role of state ownership, which does not allow large volumes of these holders to more frequently conduct transactions. Third, a report based on the Wind database notes that until 2016, such public institutional investments as mutual funds, pension investments, and insurance companies accounted for less than 1 % of the total market share. In contrast, it is believed that private investors manage more than 85% of total outstanding shares.[3] In summary, individuals hold a majority of shares. Fourth, the unified Chinese securities market is still evolving and is limited for foreign investors. In 2014, the CSRC and the Securities and Futures Commission of Hong Kong (SFC) combined China and Hong Kong's stock markets. Red chip firms, which are listed on both markets but with significantly different prices, comprise a major part of the market's capitalization, but the trading volumes across the two markets are limited to a bar. Meanwhile, the CSRC also restricts the trading volume of qualified foreign investors, such as foreign institutional investors and RMB-qualified foreign institutional investors. Finally, China's stock market trading rules are also unusual, in that the stock price's movement in each trading day is constrained to a range between an upper and lower 10%.

Given the order-driven market structure, frequently regulated policies, and special investor profile, many more inevitable consequences exist in China's stock market. First, the transaction costs and information asymmetry are more serious than in markets with market makers due to the inaccurate measurement of the bid-ask spread. Second, the market gradually becomes liquid, while different stock ownerships have distinct liquidity styles and market segregation still exists. Third, the market lacks institutional investors, and is worsened by most investors' speculative trading, with incredibly short holding periods. Investors are more likely to prefer short-term gains rather than the long-term returns from firms' future profitability. This irrational investment environment provides a natural laboratory to study the asset-pricing issue with some pricing anomalies, such as the liquidity premium, idiosyncratic volatility puzzle, idiosyncratic skewness factor, and momentum.

Fourth, although the price limit rule may avoid large fluctuations in stock prices, it facilitates various speculative trading strategies, which subsequently affects stock liquidity. The latter issue involves large firms that are often inherently capable of protecting themselves against extreme risk. Policy constraints on state-owned firms, which are often large, hinder the free sales of state-owned shares; thus, large firms' stocks are much more popular among investors due to their higher liquidity, and particularly in extreme market conditions.

In summary, a liquidity factor that transfers information, including the trading speed and cost, price impact, and trading volume as well as size effects should be considered in an asset-pricing model for China's stock market.

[3] This report was realized by the Sheng Wang Hong Yuan research center in March 2016. This report notes three categories of investors, including private investors, legal parties, and institutional investors. As legal parties primarily come from state-owned companies, which are restricted in frequently buying or selling shares, we regard investors as the remaining two types, and these types account for 42% and 7%, respectively. Regarding the U.S. market, institutional investors hold more than 45% of the total outstanding shares.

3. Methodology

3.1. Hypothesis development

This study primarily proposes that the expected stock illiquidity positively affects expected excess stock returns, or the stock return in excess of the repo rate. If investors anticipate higher illiquidity, they will price stocks to generate higher expected returns. This suggests that excess stock returns, generally regarded as the "risk premium," include premiums for illiquidity. Investors in China's financial market often transfer their money between the monetary market and stock market. As Fan and Zhang (2007) suggest, frequent arbitrage activities exist between the monetary market and the stock market. Essentially, stocks are riskier and less liquid compared to the short-term interest rates for ordinary investors in China. First, the brokerage fee is much higher for stocks than fixed-income securities, which indicates that the illiquidity costs are greater for stocks. Second, the monetary market has larger transactions, in that investors can trade tens of millions of RMB in repo products without a price impact, but block stock transactions result in price impacts that imply high illiquidity costs. Thus, the expected return on stocks in excess of the repo rates should be considered as compensation for illiquidity, in addition to its standard interpretation as compensation for risk.

Therefore, we attempt to study illiquidity effects with a panel data model, which greatly facilitates cross-sectional and time-series tests on the condition that the illiquidity data measures are available for a panel data framework. The proposition is tested by employing two hypotheses:

(I) Ex ante excess stock returns are an increasing function of expected illiquidity, and.
(II) Unexpected illiquidity negatively affects contemporaneous, unexpected stock returns.

Further, the effects of stock illiquidity on stock returns vary over time across different levels of illiquidity. In an extreme case, an increase in illiquidity during stock market crashes induces "flight-to-liquidity"; specifically, more liquid stocks decline less in value. This case is often witnessed in China's stock market: For example, China's stock market was booming at the beginning of 2007 as many investors flowed into the market. However, the growing market also faced more uncertainty due to investors' uncertain sentiment, price limit rules, and the government's intervention policies. First, the market was crowded with small investors and noisy information. This frequent information created nervous investors with irrational trading rules; thus, the stock liquidity fluctuated. Second, the price limit rule drove investors' fear of stock liquidity. Any approach of the rule's lower bound will make stock liquidity decrease to zero, and thus, investors could not freely withdraw their money. Third, regulators attempted to cool down speculation activities by often imposing unexpected policies to affect the market. For example, on May 29, 2007, the fiscal ministration tripled stock-trading tariffs, which caused the stock market to frequently experience significant crashes in that year. In some cases, such as on February 27, 2007, and May 30, 2007, the stock market index suffered more than a 7 % decline. However, large firms' stocks experienced fewer changes in illiquidity than smaller firms' stocks (Fig. 1) and caused their returns to decrease less, which corresponds to the purported "flight-to-liquidity" concept. This suggests two effects on stock returns when the expected illiquidity increases:

(III) A decrease in stock price and an increase in expected returns are common to all stocks.
(IV) Switching from less liquid to more liquid stocks creates "flight-to-liquidity."

It is noteworthy that these two effects are complimentary for low-liquid stocks, as both influence stock returns in the same direction, while the two effects operate differently for stocks with higher liquidity. An unexpected increase in stock liquidity not only negatively impacts stock prices, but also increases the relative demand for liquid stocks and mitigates their declining prices. Additionally, a higher expected stock illiquidity compels investors to demand higher expected returns; therefore, liquid stocks become relatively more attractive, decreasing the expected effect of illiquidity on their expected returns.

3.2. Estimation procedure

The ex-ante effect of liquidity on excess stock returns is described as follows:

$$\mathrm{E}(R_{it} - RF_t \mid ln\,ILLIQ_{it}^{E}) = \gamma_0 + \gamma_1 ln\,ILLIQ_{it}^{E} \tag{1}$$

where R_{it} is the logarithm of returns for stock i at time t, and $RF_t$is the spot interest rate in the same period. Stock illiquidity is denoted here by $ILLIQ_{it}$ for each time, and $lnILLIQ_{it}{}^{E}$ is the logarithm of expected stock illiquidity for stock i at time t. As discussed in Section 3.1, we assume that $\gamma_1 > 0$.

Investors are assumed to predict illiquidity at time t based on the information available in period $t-1$, and will then use this prediction to set prices to generate the desired expected returns at time t. The stock illiquidity is assumed to follow an autoregressive process

$$ln\,ILLIQ_{it} = \alpha_0 + \alpha_1 \ln ILLIQ_{it-1} + v_{it} \tag{2}$$

where v_{it} is the error term. It is intuitive to expect that $\alpha_1 > 0$.

At the beginning of time t, investors determine the expected illiquidity for the coming period based on the information at time $t-1$, and thus, expected illiquidity occurs as follows:

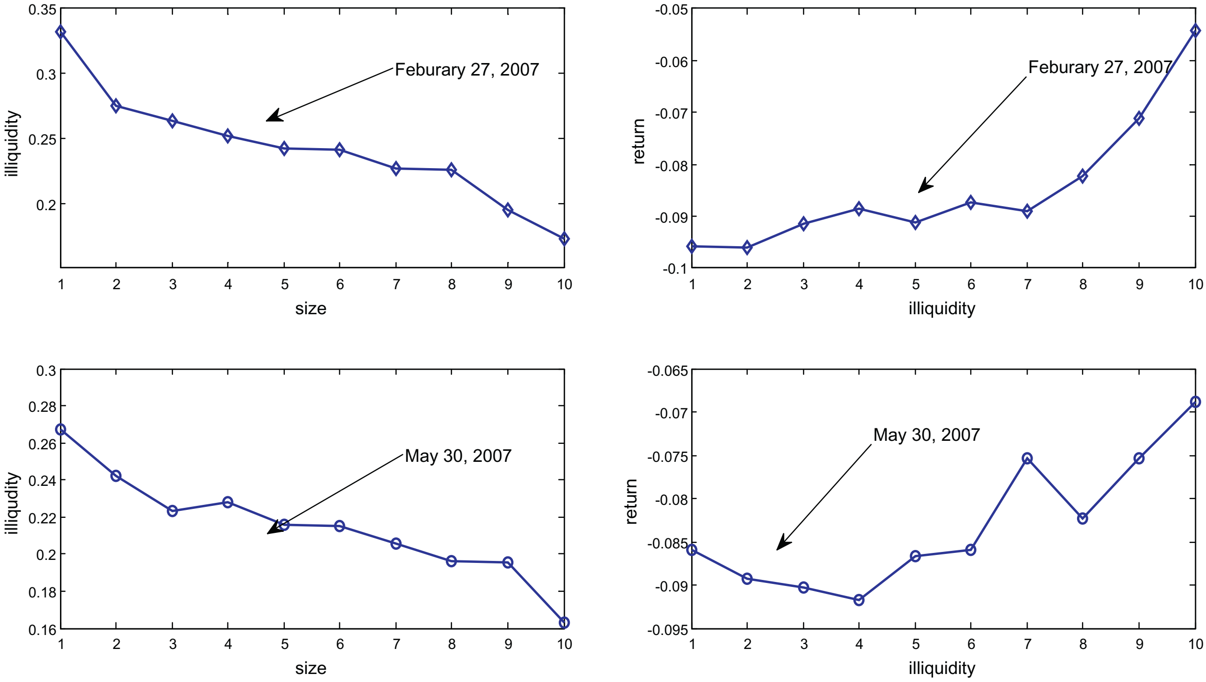

Fig. 1. Two extreme examples of "flight-to-liquidity".
Note: Illiquidity denotes the effective bid-ask spread (see Section 4.2). "Size" is the value of the firm's tradable stocks, while "return" denotes excessive stock returns. The horizontal line in each subfigure indicates the quantile of the variable, from 10% to 100%. The number on the vertical line in each subfigure is calculated from the average variable in the corresponding quantile.

$$ln\, ILLIQ_{it}^{E} = \alpha_0 + \alpha_1 \ln ILLIQ_{it-1} \tag{3}$$

Investors then set stock prices at the beginning of time t, which will generate the expected stock returns for that period. Therefore, we can obtain the assumed model, as

$$R_{it} - RF_t = \gamma_0 + \gamma_1 ln\, ILLIQ_{it}^{E} + u_{it} = \varphi_0 + \varphi_1 \ln ILLIQ_{it-1} + u_{it} \tag{4}$$

where $\varphi_0 = \gamma_0 + \gamma_1\alpha_0$ and $\varphi_1 = \gamma_1\alpha_1$. The unexpected excess returns here are denoted by the error term u_{it}. As revealed in our analysis in Section 3.1, we assume that $\varphi_1 > 0$, indicating that a higher expected illiquidity leads to higher ex-ante excess stock returns. In other words, a higher expected liquidity induces investors to demand smaller ex-ante excess stock returns.

Next, we analyze the unexpected illiquidity effect; unexpected illiquidity (or liquidity) should have a negative (or positive) impact on contemporaneous unexpected stock returns. This is because $\alpha_1 > 0$, as noted in Model (3), which means a higher illiquidity in the current period increases the expected illiquidity for the following period. If a higher expected illiquidity causes ex-ante stock returns to increase, stock prices should decrease when the illiquidity unexpectedly increases. Consequently, a negative (or positive) relationship should exist between unexpected illiquidity (or liquidity) and contemporaneous stock returns.

Hypotheses (I) and (II) in Section 3.1 are tested on the following model:

$$R_{it} - RF_t = \varphi_0 + \varphi_1 \ln ILLIQ_{it-1} + \varphi_2 \ln ILLIQ_{it}^{U} + \varphi_t + w_{it} \tag{5}$$

where $\ln ILLIQ_{it}^{U}$ denotes the unexpected illiquidity at time t, and $\ln ILLIQ_{it}^{U} = \hat{v}_{it}$, or the residual from Model (2); φ_t indicates the time-fixed effects (year, month, or weekday). Thus, Hypotheses (I) and (II) can be demonstrated as follows:

$H1: \varphi_1 > 0$, and $H2: \varphi_2 < 0$.

Specifically, the coefficient φ_1 is positive and significant, suggesting that expected stock illiquidity positively affects excess returns; the coefficient φ_2 is negative and significant, suggesting that unexpected stock illiquidity negatively influences stock prices.

We further consider the size's effect on the relationship between stock illiquidity and excess returns. Hypotheses (III) and (IV) in Section 3.1 can be tested on the following model by introducing the size variable into Model (5):

$$\mathrm{R_{it} - RF_t = \varphi_0 + (\varphi_1 + \varphi_4 Size_{it}) \ln ILLIQ_{it-1} + (\varphi_2 + \varphi_5 Size_{it}) lnILLIQ_{it}^{U} + \varphi_3 Size_{it} + \varphi_t + e_{it}} \tag{6}$$

where $Size_{it}$ denotes the size of stock i in time t. The proposition that the illiquidity effect is stronger for the small illiquid stocks implies two predictions in Model (6):

$H3: \varphi_4 < 0$, and $\mathrm{H4}: \varphi_5 > 0$.

Specifically, the coefficient φ_4 is negative and significant, suggesting that the positive effects of expected stock illiquidity on excess return would decrease as firms become larger; the coefficient φ_5 is positive and significant, suggesting that unexpected stock illiquidity's negative effects on excess returns would weaken for larger firms.

Stockholders in China's stock market are primarily comprised of private investors, and they prefer to hold stocks in anticipation of obtaining higher individual returns than in the market portfolio; otherwise, they will invest their money in market portfolios to earn market returns. Therefore, the stocks' expected returns should compensate for illiquidity as well as market risk. We confirm the size effects' robustness by introducing market risk to Model (6); further, we develop Model (7) as

$$\mathrm{R_{it} - RF_t = \varphi_0 + (\varphi_1 + \varphi_4 Size_{it})\ln ILLIQ_{it-1} + (\varphi_2 + \varphi_5 Size_{it})lnILLIQ^U_{it} + \varphi_3 Size_{it} + \varphi_6 Rmrf_t + \varphi_t + \epsilon_{it}} \tag{7}$$

where $Rmrf_t$ is the excess market returns in time t.

Each of our estimations adopts a fixed-effects model controlling for firm-fixed (or stock) effects to alleviate endogenous concerns from omitting the variable bias. Moreover, robust standard errors are clustered at the firm (stock) level to address any possible heteroskedasticity and serial correlation.

4. Data and variables

4.1. Data source and definition of some variables

The intraday high-frequency data utilized in this paper was derived from the China Security Market Trade & Quote Research Database (CSMAR) from January 1, 2006, to September 30, 2015. The CSMAR covers every quotation and execution price for all A-share-traded stocks in the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). These quotations and prices are time-stamped to the nearest second and updated within five seconds on average. This database also provides information on trading volume and bid and ask prices. Other data for this study was collected from the RESSET database from January 1, 2001, to September 30, 2015, and includes stock returns, the repo rate, market returns, turnover rates, and firm size.

As mentioned in Section 3.2, excess stock returns (*Re*) are defined as the logarithm of return for a stock minus the repo rate; we take this variable as the dependent variable in our later estimations. Similarly, the excess market returns (*Rmrf*) are constructed by a logarithmic return for the entire market minus the repo rate. We also adopt the value of a firm's tradable stocks as *Size*, a proxy for firm (stock) size.

4.2. Liquidity measures

Liquidity is notoriously difficult to measure with precision. Liu (2006) defines liquidity as “an ability to trade large quantities quickly at low cost with little price impact.” Therefore, liquidity encompasses at least five dimensions: asymmetric information, trading quantity, transaction costs, trading speed, and price impact. As described in Section 2, any single measure of liquidity in China's stock market cannot capture all of these aspects, resulting in biased estimations in empirical studies (Amihud et al., 2015). Therefore, we consider several measures of liquidity, including those calculated from both high frequency and low-frequency data.

Bid-ask spreads. High frequency bid-ask spreads are an ideal proxy for liquidity, and are regarded as direct liquidity measures. We calculate the time-weighted quoted (*Qsp*) and effective bid-ask spreads (*Esp*) for each individual stock on each trading day, using the time intervals between two consecutive quotations as the respective weights, following work by Mcinish and Wood (1992). Further, we calculate closing bid-ask spreads by using the last quotation (*Qsp_c*, *Esp_c*) in each respective trading day. The quoted and effective spreads are defined as follows:

$$Qsp = 2 \times \frac{S_1 - B_1}{S_1 + B_1} \times 100\%$$

$$Esp = 2 \times \frac{|P_t - \frac{S_1 + B_1}{2}|}{S_1 + B_1} \times 100$$

where S_1 is the ask price, B_1 is the bid price, and P_t is the stock trading price in the time interval. These four illiquidity measures are first given in the daily time horizon, and those in the monthly and annual time horizons are the sample averages of the former. Compared with the time-weighted bid-ask spread measures, the closing bid-ask spread measures contain less information on intraday microstructure noise, and only provides information regarding the last trade or quotation. These four illiquidity measures were sampled from January 1, 2006, to September 30, 2015.

As China's stock market is an order-driven market and the majority of traders are private investors, asymmetric information is the primary source to affect the bid-ask spreads. Therefore, bid-ask spreads can be observed as an illiquidity measure in the trading cost and asymmetric information dimensions (Goyenko et al., 2009; Zhang et al., 2013). The higher the bid-ask spread, the more illiquid the stock.

Roll effective spread (*Roll*). The relative bid-ask spread merely captures the cost of immediacy, but not all trades are complete at the best price limits. Hence, the bid-ask spread in an order-driven market may not provide each trade's exact transaction cost. We address these concerns by introducing Roll's (1984) effective spread estimator. Roll (1984) found that stock prices change with the native covariance of return. Hence, a stock's auto-covariance may be suitable to measure that stock's effective spread. It is noteworthy that this illiquidity measure is calculated using daily data, and thus, is only available at monthly and annual horizons. The larger the *Roll*, the more illiquid the stock.

Trade volume (Volume). This is defined as the number of share traded in each period times the share's price, denoting the trading volume dimension of liquidity. The larger the trading volume, the more liquid the stock.

Turnover rate (Turnover). Datar et al. (1998) provide an alternative test for Amihud and Mendelson's (1986) model by using turnover rates as a proxy of illiquidity. This paper considers daily as well as monthly and yearly average turnover rates as alternative measures of illiquidity. The higher the turnover rate, the more liquid the stock, which is similar to trading volume (*Volume*) but functions opposite to bid-ask spreads. This illiquidity measure is often used to indicate stocks' trading speed.

Percentage of zero returns (Zeros). According to Lesmond and Trzcinka (1999), the likelihood of trading for a given amount of information declines when facing higher transaction costs. By studying the liquidity-expected return relationship of 19 emerging markets, Bekaert et al. (2007) documented that zeros highly correlate with other liquidity measures. We also use *Zeros*, or the percentage of zero-return days within an entire month or year adjusted for trading days, as a proxy for liquidity in this paper. This measure closely relates to the price limit in China's stock market, and is often used to represent the illiquidity caused by price impacts. The larger the *Zeros*, the higher the stock's illiquidity.

Amihud's illiquidity measure (Amihud). Amihud (2002) measures liquidity as the average ratio of the daily absolute return to the dollar trading volume on that day. Intuitively, this ratio can be interpreted as the price impact induced by a given dollar volume. As this measure often displays extreme values, Hasbrouck (2009) provided a modified measurement: the average of the square roots of daily ratios. The present paper follows Hasbrouck's (2009) work to construct an index for each stock by averaging the price impact ratio over each day. The greater the *Amihud*, the greater the stock's illiquidity.

In summary, the above liquidity measures capture the dimensions of illiquidity, including transaction costs, asymmetric information, trading volume, trading speed, and price impacts. Tables A1–A3 in the Appendix list the statistics for these variables—including yearly, monthly, and daily horizons, respectively—and each of these tables contains two panels: a cross-section and time series.[4]

We further illustrate these variables' other features by calculating the data's mean by year, month, and weekday. Fig. 2 (Panels A to C) illustrates that regarding the annual scope, the illiquidity measures—including the bid-ask spread, trading volume, turnover rate, *Amihud*, and *Roll*—correlate with the excess returns, which fluctuate over time. Additionally, as aforementioned in Section 2, the average liquidity has improved for recent years. Regarding the monthly scope, as Fig. 2 (Panels D to F) illustrates, we find that the co-movement between liquidity and excess returns is similar to that of annual data. In contrast, the weekday description in Fig. 2 (Panels G to I) reveals that the movements of illiquidity are not as volatile as the excess returns. These stylized facts have piqued our interest to investigate the illiquidity effects among different time scopes.

In summary, the correlations between direct and indirect illiquidity measures vary over time scopes. Thus, these two types of illiquidity measures' effects on asset pricing may differ across time horizons. However, most existing studies on the relationship between stock illiquidity and asset pricing do not comprehensively consider these facts. Therefore, the next section will examine whether illiquidity's effects on asset pricing change across different illiquidity measures and time scopes by using the empirical strategy described in Section 3.2.

5. Results

This section first tests the relationship between illiquidity and stock returns by using annual data. The same procedure is then applied to the monthly and daily data, respectively. Finally, similar analyses are replicated after additionally controlling for market risk.

5.1. Illiquidity's effects on stock returns, based on annual data

5.1.1. Illiquidity's effects on excessive stock returns

We conduct two exercises to estimate the relationship between illiquidity and excessive stock returns, referring to work by Amihud (2002). We first estimate $\hat{v}_{it}$ from Model (2), and $\hat{v}_{it}$ is then used as a proxy of unexpected illiquidity, $\ln ILLIQ_{it}{}^{U}$, to estimate φ_1 and φ_2 from Model (5).

Panel A in Table 1 reports the results from our first step; Panel A reveals that all of these illiquidity measures have positive, significant coefficients. However, the direct illiquidity measures have smaller coefficients than those of the indirect illiquidity measures, and especially for *Esp* and *Qsp*. This suggests that if illiquidity measures are used to form expectations of future illiquidity, indirect measures provide more information than those involving direct illiquidity.

Panel B in Table 1 presents our second step's results. We find that Hypothesis H1 is supported by all nine liquidity measures, and Hypothesis H2 is satisfied by *Esp_c, Qsp_c, Turnover, Volume,* and *Zeros*. The model with the *Amihud* measure only supports Hypothesis H1; this signifies that the negative relationship between unexpected illiquidity and stock returns at the annual scope is not as robust as we anticipated in China's stock market, as opposed to the U.S. market as presented by Amihud (2002).

[4] In the Appendix, we also describe the intraday data in detail following two ways. Firstly, we demonstrate general knowledge on the intraday data by providing four figures in Section 2 in the Appendix, which illustrate the stock prices' dynamics, the volume for each trading tick, and the bid-ask spread. Then, we provide the additional descriptive statistics for intraday data across the whole samples with different sampling frequency in Section 3 in the Appendix.

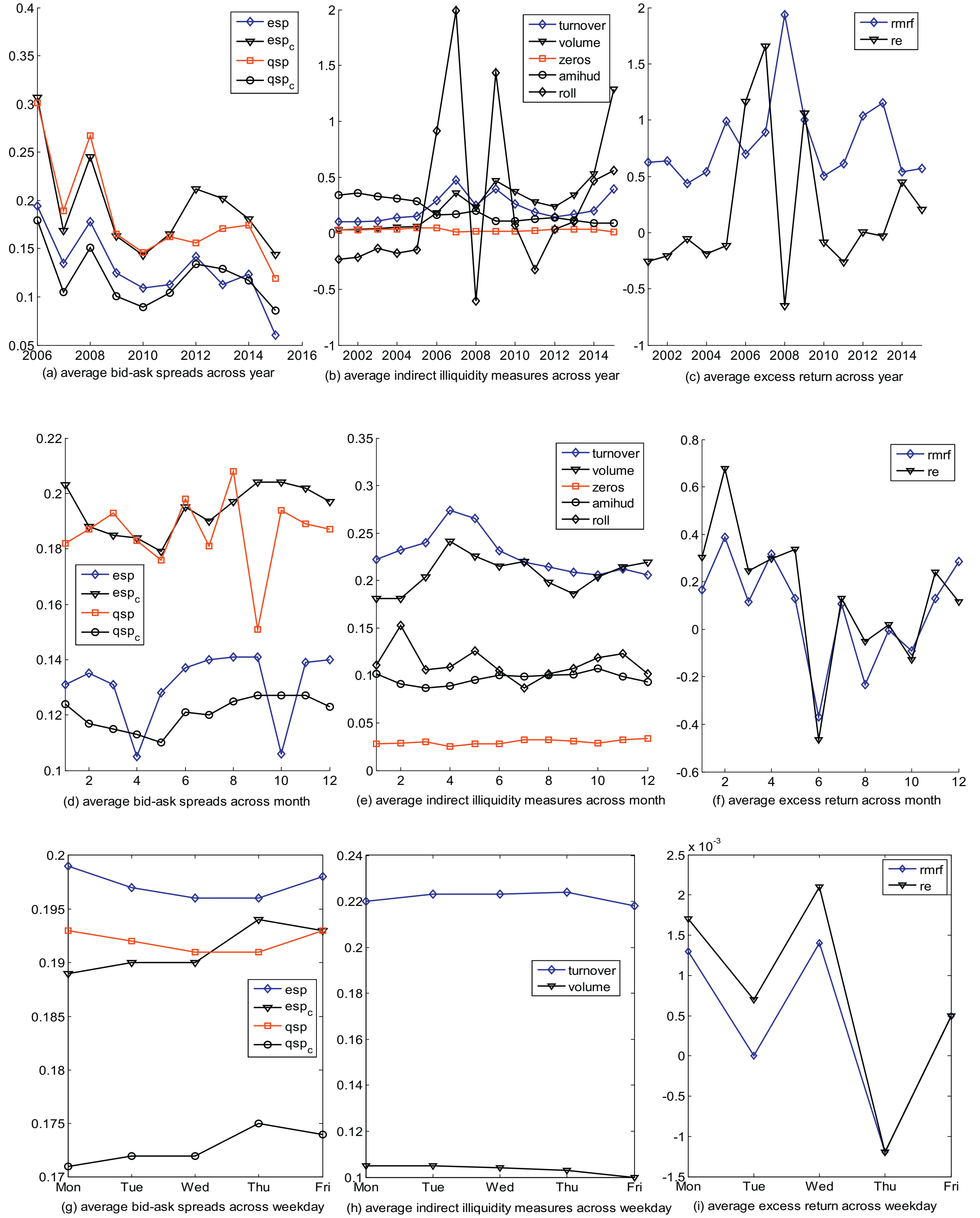

Fig. 2. Illiquidity measures and excess returns over time.

Notes: The variables' data and definitions are the same as those in the Appendix, Tables A1–A3. These variables' average levels are derived by calculating the average values of each year, month, and weekday. The magnitude of indirect liquidity measures are uniform to the same measurement unit in subplots (b), (e), and (h). Further, *Rmrf* and *Re* are the excessive market returns and excessive stock returns, respectively, which are calculated by multiplying by 100, except in subplots (g to i).

Table 1
Estimations based on Models (2) and (5) using annual data.

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Estimations based on Model(2)									
α_1	0.202***	0.226***	0.091***	0.231***	0.051***	0.830***	0.545***	0.254***	0.752***
	(11.48)	(23.70)	(5.15)	(23.39)	(3.91)	(179.64)	(71.59)	(33.86)	(115.50)
α_0	−1.665**	−1.410***	−1.626***	−2.690***	0.007***	−0.331***	−0.756***	−2.785***	0.020***
	(−46.65)	(−85.93)	(−54.26)	(−80.54)	(50.11)	(−21.31)	(−54.21)	(−100.80)	(6.43)
R^2	0.032	0.065	0.007	0.065	0.003	0.649	0.300	0.059	0.543
N	11,710	11,952	11,237	11,951	8091	17,997	17,997	16,989	17,997
Panel B: Estimations based on Model(5)									
φ_1	0.333***	0.548***	0.192***	0.581***	0.020*	−0.073***	−0.007	0.109***	0.186***
	(10.74)	(14.64)	(10.62)	(15.76)	(1.73)	(−7.93)	(−0.68)	(12.21)	(9.55)
φ_2	0.055***	−0.246***	0.029**	−0.333***	0.164***	0.138***	0.220***	−0.083***	0.318***
	(3.00)	(−6.53)	(2.15)	(−8.85)	(7.45)	(11.13)	(17.08)	(−9.59)	(12.53)
φ_0	2.613***	2.694***	2.288***	3.670***	−0.180***	−0.491***	−0.113***	0.202***	−0.538***
	(37.60)	(42.71)	(51.25)	(31.15)	(−14.81)	(−10.17)	(−4.66)	(6.12)	(−19.20)
Year-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.645	0.647	0.645	0.652	0.613	0.622	0.622	0.626	0.621
N	11,710	11,952	11,237	11,951	8091	17,997	17,997	16,989	17,997

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are noted in parentheses. Robust standard errors are clustered at the firm (or stock) level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

5.1.2. Illiquidity's effects on excess stock returns, considering size effects

As mentioned in Hypotheses H3 and H4, small, illiquid stocks should experience stronger effects from stock illiquidity; specifically, the expected illiquidity should have a larger, positive effect on ex-ante returns, while unexpected illiquidity should more negatively affect contemporaneous returns. Both effects should be weaker for large, liquid stocks, as these stocks become relatively more attractive in times of dire illiquidity. We test these arguments by estimating the firm size's effects on the relationship between stock illiquidity and excess returns, based on Model (6).

The results noted in Table 2 are consistent with both Hypotheses H3 and H4 by adopting the high-frequency illiquidity measures (*Qsp* and *Esp*) and Amihud illiquidity measure. Specifically, the coefficients φ_4 are negative and significant in those estimations, suggesting that the stock illiquidity's return-improving effect decreases as the firm size increases. Further, the coefficients φ_5 are positive and significant, indicating that the unexpected illiquidity's effects weaken as the firm size increases.

Our findings confirm that the effects of stock illiquidity—both expected and unexpected—are stronger for small firms than for larger firms, which directly proves the "flight-to-liquidity." This also signifies that small firms have a greater illiquidity risk. If this risk is priced in the market, then stocks with greater illiquidity risk should earn higher illiquidity risk premiums, as argued by Pástor and Stambaugh (2003). This also helps to explain why small stocks on average earn higher expected returns. By analyzing stock

Table 2
Estimations based on Model (6) using annual data.

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
φ_4	−4.174***	−0.140	−6.596***	2.753*	1.972	0.189*	−0.401	−1.311***	−0.621**
	(−3.63)	(−0.09)	(−3.07)	(1.89)	(0.62)	(1.67)	(−1.20)	(−2.85)	(−2.40)
φ_5	3.864***	−1.015	6.078***	−3.548*	−1.705	0.204	0.673*	0.364	1.037***
	(3.06)	(−0.54)	(2.71)	(−1.89)	(−0.53)	(1.20)	(1.82)	(0.76)	(3.47)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
F-statistics	1420.37	1559.45	1371.40	1592.88	411.69	1188.98	1253.78	1228.85	1106.45
R^2	0.646	0.649	0.647	0.653	0.614	0.623	0.623	0.629	0.623
N	11,705	11,947	11,232	11,946	8089	17,992	17,992	16,984	17,992

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are noted in parentheses. The *F-statistics* are derived from the joint significance test of the new variables in Model (6), relative to Model (5). Robust standard errors are clustered at the firm (or stock) level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3
Estimations based on Models (2) and (5) using monthly data.

	Esp[*,**]	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Estimations based on Model (2)									
α_1	0.527***	0.664***	0.510***	0.760***	0.196***	0.893***	0.782***	0.119***	0.871***
	(69.97)	(22.95)	(63.75)	(225.73)	(40.41)	(628.29)	(347.93)	(17.33)	(381.94)
α_0	−0.974***	−0.604***	−0.852***	−0.829***	−1.479***	−0.352***	−0.425***	−2.337***	−0.049***
	(−62.90)	(−11.69)	(−61.51)	(−71.87)	(−167.02)	(−73.01)	(−97.23)	(−127.90)	(−72.04)
R^2	0.285	0.446	0.262	0.581	0.039	0.801	0.628	0.014	0.766
N	141,612	144,453	137,374	144,404	70,400	223,534	223,534	43,928	223,499
Panel B: Estimations based on Model (5)									
φ_1	0.043***	0.038***	0.030***	0.045***	0.005***	0.009***	0.013***	0.004***	−0.017***
	(33.49)	(11.07)	(29.24)	(41.16)	(6.33)	(31.83)	(29.78)	(3.13)	(−24.82)
φ_2	−0.031***	−0.062***	−0.039***	−0.109***	0.024***	0.099***	0.108***	−0.006***	−0.166***
	(−17.19)	(−6.74)	(−26.68)	(−43.14)	(28.51)	(116.52)	(123.28)	(−5.64)	(−84.79)
φ_0	0.130***	0.108***	0.095***	0.192***	0.039***	0.052***	0.047***	0.041***	0.032***
	(45.74)	(18.30)	(45.04)	(49.27)	(17.63)	(40.64)	(39.82)	(11.32)	(38.05)
Month-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.074	0.087	0.079	0.113	0.065	0.203	0.220	0.037	0.148
N	141,612	144,453	137,374	144,404	70,400	223,534	223,534	43,928	223,499

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are noted in parentheses. Robust standard errors are clustered at the firm (or stock) level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

illiquidity's heterogeneous effects on excess returns across firm sizes, we can appropriately capture how illiquidity impacts stock returns.

5.2. Illiquidity's effects on stock returns, based on monthly data

This subsection replicates the procedure in Section 5.1, but the current procedure uses monthly data, with 180 months (120 months for direct illiquidity measures) during the period of 2001 to 2015.

Panel A in Table 3 presents the results estimated based on Model (2) with monthly data, which substantially differs from those using annual data. In this panel, $\alpha_1 > 0$ and the coefficients are more than or approximate to 0.6 in most columns. These results suggest that the stock illiquidity's positive effect on excess returns is enhanced after replacing annual data with monthly data. Specifically, the high-frequency illiquidity measures are more conducive to forming expected illiquidity.

The results in Panel B of Table 3 reveal that the models with four direct illiquidity measures and *Zeros* have coefficients of $\varphi_1 > 0$ and $\varphi_2 < 0$, and all of them are significant. However, other illiquidity measures do not generate robust results, such as $\varphi_1 > 0$ and $\varphi_2 > 0$ for the *Roll* illiquidity measure and $\varphi_1 < 0$ and $\varphi_2 < 0$ for the *Amihud* illiquidity measure. Therefore, the models with

Table 4
Estimations based on Model (6) using monthly data.

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
φ_4	−4.682***	−4.795***	−4.723***	−0.790***	0.492*	0.839***	1.929***	−0.989**	−0.625***
	(−10.27)	(−4.73)	(−13.72)	(−4.49)	(1.68)	(10.19)	(16.42)	(−2.25)	(−3.47)
φ_5	−3.216***	3.998***	−0.236	2.331***	0.551*	0.598**	1.348***	1.310***	4.611***
	(−4.75)	(3.06)	(−0.42)	(3.25)	(1.68)	(2.32)	(5.05)	(2.89)	(7.14)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
F-statistics	791.49	770.00	748.35	807.98	355.37	1806.98	1817.88	103.77	1310.59
R^2	0.076	0.089	0.081	0.115	0.067	0.205	0.223	0.038	0.151
N	141,612	144,453	137,374	144,404	70,400	223,533	223,533	43,928	223,499

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are in parentheses. The *F-statistics* are derived from the joint significance test of the new variables in Model (6), relative to Model (5). Robust standard errors are clustered at the firm (or stock) level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5
Rolling window estimations based on Model (6) using monthly data.

	Esp			*Esp_c*			*Qsp*		
	Full	Mean	Median	Full	Mean	Median	Full	Mean	Median
φ_4	−4.73	−3.26	−3.39	−4.84	−3.26	−3.53	−4.78	−0.11	−2.17
φ_5	−3.23	−2.58	−1.82	4.05	4.11	4.01	−0.24	−6.06	−3.28
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

	Qsp_c			*Roll*			*Turnover*		
	Full	Mean	Median	Full	Mean	Median	Full	Mean	Median
φ_4	−0.81	−1.11	−1.30	0.49	−0.80	−1.19	0.84	0.67	0.56
φ_5	2.42	4.60	5.70	0.55	−0.56	−0.39	0.61	−1.28	−1.28
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

	Volume			*Zeros*			*Amihud*		
	Full	Mean	Median	Full	Mean	Median	Full	Mean	Median
φ_4	1.95	1.00	0.61	−1.00	−0.24	−0.39	−0.62	−1.63	−1.65
φ_5	1.37	−0.96	−0.97	1.33	2.23	2.06	4.61	5.68	5.64
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The "Full" column is the benchmark estimation using the full sample; the other two "Mean" and "Median" columns note the estimated coefficients' mean and the median using the rolling window.

monthly data tend to support the hypotheses by using high-frequency illiquidity measures rather than the *Roll* and *Amihud* measures.

The illiquidity's size effect is then tested based on Model (6) by replacing the size variable in the monthly frequency; Table 4 documents the results. This table indicates that the models with two direct measures (*Esp_c and Qsp_c), Zeros,* and *Amihud* satisfy Hypotheses H3 and H4. These results suggest that more evidence supporting Hypotheses H3 and H4 are provided in the analysis based on monthly data rather than annual data. This finding is consistent with that in Amihud's (2002) work.

As a robustness check, we further define a subsample window of 70 months for direct illiquidity measures, or 130 months for the indirect measures, and roll the window every 12 months. Therefore, five subsamples are picked up, and Model (6) is re-estimated with each subsample. Table 5 reports the mean and median of the coefficients estimated using these rolling samples. This table indicates that the mean and median of coefficients φ_4 and φ_5 estimated by these rolling samples have signs consistent with those estimated by the full sample for almost all illiquidity measures. Further, the estimation results from the direct illiquidity, *Zeros*, and *Amihud* measures are more robust than other measures.

5.3. Illiquidity's effect on stock returns, based on daily data

The previous subsection's procedure is replicated here, but with daily data; the period of 2001 to 2015 includes 3671 days, or 2493 days for direct illiquidity measures.

Table 6 presents the results using daily data, which are qualitatively similar to those calculated using monthly data. Specifically, the four high-frequency illiquidity measures have coefficients $\varphi_1 > 0$ and $\varphi_2 < 0$, and all of them are significant. Therefore, the estimated results with high-frequency illiquidity measures and based on daily data support Hypotheses H1 and H2.

We further test the size effects based on Model (6) by using daily data, and Table 7 displays the results. This table reveals that $\varphi_4 < 0$ and $\varphi_5 > 0$ only hold in models adopting *Qsp_c* and *Turnover* as proxies of illiquidity, while models adopting other illiquidity measures do not indicate such consistent results. These findings differ from those in the cases of annual and monthly data.

As a robustness check, we define a window of 1670 trading days, and roll every 500 trading days to pick up a sample window. Thus, five subsamples are defined, and Model (6) is re-estimated for each subsample. Table 8 reports the mean and median of coefficients estimated by those rolling window samples. The results indicate that for most of the illiquidity measures, the mean and median of coefficients estimated by those rolling window samples have signs consistent with those estimated by the full sample, except for φ_5 in some models. These estimations confirm the robustness of the results based on daily data.

5.4. Size effects, controlling for market risk

Until now, we have not considered the market factor's effect on the asset-pricing model. The market factor is also an essential part of the pricing model, such as in Liu's (2006) two-factor model. This subsection further checks whether the "flight-to-liquidity" phenomenon still exists after controlling for the market portfolio returns.

Tables 9–11 display the estimations based on Model (7). These tables indicate that the market returns' coefficients are positive and significant, suggesting that stock returns also a catalyst for market risk. More importantly, the models adopting *Esp*, *Qsp,* and *Amihud*

Table 6
Estimations based on Models (2) and (5) using daily data.

	*Esp****	*Esp_c*	*Qsp*	*Qsp_c*	*Turnover*	*Volume*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Estimations based on Model (2)						
α_1	0.879***	0.088***	0.899***	0.495***	0.875***	0.930***
	(468.85)	(43.86)	(583.24)	(78.43)	(841.42)	(1248.65)
α_0	−0.210***	−1.811***	−0.180***	−1.005***	0.024***	0.075***
	(−64.61)	(−452.15)	(−65.99)	(−79.94)	(116.65)	(93.22)
R^2	0.845	0.065	0.869	0.439	0.792	0.897
N	2,864,752	2,825,978	2,864,758	2,794,847	4,388,757	4,388,757
Panel B: Estimations based on Model (5)						
φ_1	2.10***	0.22***	1.83***	1.06***	0.43***	0.39***
	(21.69)	(14.94)	(19.03)	(16.74)	(18.52)	(24.84)
φ_2	−36.15***	−0.71***	−44.62***	−5.48***	15.85***	15.07***
	(−69.22)	(−39.15)	(−69.33)	(−63.08)	(140.78)	(130.80)
φ_0	4.92***	1.36***	5.94***	5.11***	0.45***	0.12***
	(28.64)	(30.95)	(33.47)	(37.64)	(17.68)	(3.81)
Weekday-Fixed Effects	yes	yes	yes	yes	yes	yes
R^2	0.042	0.003	0.061	0.011	0.074	0.071
N	2,864,752	2,825,978	2,864,758	2,794,847	4,388,751	4,388,751

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are noted in parentheses. Robust standard errors are clustered at the firm (or stock) level. All coefficients are multiplied by 10^3.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 7
Estimations based on Model (6) using daily data.

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Turnover*	*Volume*
	(1)	(2)	(3)	(4)	(5)	(6)
φ_4	0.035***	−0.001	−0.024	−0.030*	−0.050***	0.107***
	(2.78)	(−0.28)	(−1.49)	(−1.69)	(−4.06)	(5.35)
φ_5	0.080	0.011***	0.446**	0.095**	0.277**	0.420***
	(0.84)	(3.92)	(2.51)	(2.49)	(2.41)	(3.53)
Other Variables	yes	yes	yes	yes	yes	yes
Weekday-Fixed Effects	yes	yes	yes	yes	yes	yes
F-statistics	6.579	8.805	4.576	6.154	28.278	10.173
R^2	0.044	0.004	0.063	0.012	0.075	0.072
N	2,855,163	2,816,575	2,855,169	2,785,258	4,378,295	4,378,295

Notes: All the regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are noted in parentheses. The *F-statistics* are derived from the joint significance test of the new variables in Model (6), relative to Model (5). Robust standard errors are clustered at the firm (or stock) level. All coefficients are multiplied by 10^3.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

as proxies of illiquidity generally support Hypotheses H3 and H4 in the annual horizon, which is consistent with their counterparts in Table 2. Regarding the monthly horizon, the sign and significant of coefficients of our key variables are similar to the earlier results. Further, only the results from the *Amihud* illiquidity measure remain significant to support all hypotheses. The daily horizon model with *Qsp_c* does not support H3 and H4 compared to the model in Table 7, while the model with a turnover measure still confirms these two hypotheses.

The above results also suggest the importance of including excess market returns in testing these hypotheses at the year level, as the market's excessive returns signify the market's systematic risk. This finding explains some long-term effects, and long-term investors primarily consider this as an important pricing factor. Market illiquidity in the short-term is rarely regarded as a source of risk.

Overall, illiquidity positively affects excess stock returns, and this impact is larger for less-liquid stocks or smaller firms. Moreover, the high frequency bid-ask spreads are better measures of illiquidity in estimating the relationship between illiquidity and excess stock returns. The size effect denoting “flight-to-liquidity” is also robust to market risk.

Table 8
Rolling window estimations based on Model (6) using daily data.

	Esp			*Esp_c*			*Qsp*		
	Full	Mean	Median	Full	Mean	Median	Full	Mean	Median
φ_4	0.04	0.07	0.06	0.00	−0.01	0.00	−0.02	−0.02	−0.02
φ_5	0.08	0.12	0.18	0.01	0.02	0.01	0.45	0.63	0.64
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

	Qsp_c			*Turnover*			*Volume*		
	Full	Mean	Median	Full	Mean	Median	Full	Mean	Median
φ_4	−0.03	−0.04	−0.03	−0.05	0.07	0.03	0.11	0.08	0.12
φ_5	0.10	0.12	0.11	0.28	0.16	−0.13	0.42	0.16	0.05
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The "Full" column illustrates the benchmark estimation with the full sample; the other two "Mean" and "Median" columns display the mean and median of the estimated coefficients with the rolling window. All coefficients are multiplied by 10^3.

Table 9
Estimations based on Model (7) using annual data.

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
φ_4	−4.439***	−0.292	−6.962***	2.838*	1.910	0.193*	−0.409	−1.315***	−0.570**
	(−3.81)	(−0.19)	(−3.25)	(1.95)	(0.59)	(1.66)	(−1.20)	(−2.83)	(−2.41)
φ_5	4.129***	−0.881	6.437***	−3.657*	−1.636	0.160	0.653	0.345	1.088***
	(3.23)	(−0.46)	(2.89)	(−1.95)	(−0.51)	(0.82)	(1.64)	(0.71)	(3.58)
φ_6	0.011***	0.008**	0.013**	0.008**	0.005***	0.002	0.002	0.004***	0.008***
	(64.91)	(2.32)	(2.31)	(2.38)	(3.30)	(1.09)	(0.64)	(3.91)	(4.46)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.646	0.649	0.647	0.653	0.614	0.623	0.623	0.629	0.624
N	11,705	11,947	11,232	11,946	8089	17,992	17,992	16,984	17,992

Note: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are in parentheses. Robust standard errors are clustered at the firm (or stock) level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 10
Estimations based on Model (7) using monthly data.

	*Esp**	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
φ_4	−2.309***	−3.104***	−2.294***	−0.392***	1.685***	1.429***	3.272***	−1.940***	−1.531***
	(−6.58)	(−7.27)	(−8.71)	(−2.73)	(6.85)	(16.86)	(29.02)	(−5.29)	(−8.54)
φ_5	−1.309**	0.751	−0.876**	0.690	1.420***	−0.151	1.097***	−0.414	1.720***
	(−2.49)	(1.36)	(−2.36)	(1.19)	(5.02)	(−0.64)	(4.45)	(−1.14)	(3.41)
φ_6	0.011***	0.011***	0.011***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(198.09)	(180.25)	(194.71)	(197.56)	(168.41)	(207.51)	(208.33)	(127.21)	(193.07)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.453	0.452	0.455	0.457	0.489	0.493	0.497	0.439	0.449
N	141,612	144,453	137,374	144,404	70,400	223,533	223,533	43,928	223,499

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are in parentheses. Robust standard errors are clustered at the firm (or stock) level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 11
Estimations based on Model (7) using daily data.

	*Esp***	*Esp_c*	*Qsp*	*Qsp_c*	*Turnover*	*Volume*
	(1)	(2)	(3)	(4)	(5)	(6)
φ_4	0.015	0.006	−0.003	0.013	−0.040*	0.066***
	(0.37)	(1.16)	(−0.06)	(0.68)	(−1.95)	(3.64)
φ_5	0.620***	0.025***	0.936***	0.084***	0.354***	0.457***
	(3.04)	(4.05)	(3.17)	(2.86)	(2.61)	(3.39)
φ_6	1.071***	1.130***	1.096***	1.118***	1.127***	1.129***
	(293.97)	(288.19)	(290.98)	(276.74)	(342.74)	(342.81)
Other Variables	yes	yes	yes	yes	yes	yes
Weekday-Fixed Effects	yes	yes	yes	yes	yes	yes
F-statistics	86,418.88	83,054.38	84,669.70	76,586.68	117,472.22	117,522
R^2	0.417	0.409	0.418	0.407	0.442	0.440
N	2,855,163	2,816,575	2,855,169	2,785,258	4,378,295	4,378,295

Note: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are in parentheses. Robust standard errors are clustered at the firm (or stock) level. All coefficients are multiplied by 10^3.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

6. Extension

We have discovered significant evidence regarding the "flight-to-liquidity" under wide examinations, and particularly for monthly data. This section further explores the relationship between the "flight-to-liquidity" phenomenon and some important financial anomalies, including the idiosyncratic volatility puzzle (Ang et al., 2009; Long et al., 2018), gambling behavior (Boyer et al., 2007, 2010; Cao, 2015), and momentum effects (Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Lu and Zhou, 2007). These topics have attracted more concern in stock markets worldwide. We analyze such relationships by introducing a variable to represent idiosyncratic volatility (*Iv*), idiosyncratic skewness (*Is*), and momentum (*Mom*) into Model (7), respectively. Thus, Model (8) is developed as:

$$R_{it} - RF_t\varphi_0 + (\varphi_1 + \varphi_4 Size_{it}) \ln ILLIQ_{it-1} + (\varphi_2 + \varphi_5 Size_{it}) \ln ILLIQ_{it}^{U} + \varphi_3 Size_{it} + \varphi_6 Rmrf_{it} + \varphi_7 F_{it} + \varphi_t + \varepsilon_{it} \tag{8}$$

where F_{it} is one of the variables for idiosyncratic volatility (*Iv*), idiosyncratic skewness (*Is*), and momentum (*Mom*).[5]

We then test these relationships by comparing Model (8) with and without the variables that signify the "flight-to-liquidity." If the significance and magnitude of the coefficients for idiosyncratic volatility, idiosyncratic skewness, or momentum decrease in absolute value after considering size effects, we can infer that the "flight-to-liquidity" can explain them. Tables 12–14 report these test results.

Panel A in Table 12 reveals idiosyncratic volatility as significantly negative, denoting the existence of an "idiosyncratic volatility puzzle." However, after controlling for two items expressly related to the "flight-to-liquidity"—the interactions of firm size and illiquidity—most columns in Panel B display weaker significances for the coefficient φ_7, in that the *t*-statistics decreased; and, the magnitudes of φ_7 also become smaller. These changes are particularly apparent in models with high-frequency bid-ask spreads as illiquidity measures; this implies that the "flight-to-liquidity" induced by transaction costs and asymmetric information partially explains the idiosyncratic volatility puzzle. This new mechanism to explain this puzzle differs from existing literature, which emphasizes U.S. markets' risk preferences (Vorkink, 2007; Barberis and Huang, 2008; Kumar, 2009), the heterogeneous beliefs of Chinese stock holders (Huang et al., 2006; Chen et al., 2013; Long et al., 2018), and market frictions of China's stock market (Gu et al., 2018).

Comparatively, institutional investors have more advantages in acquiring stock information than private investors. Too many noisy private investors in the stock market can degrade the asymmetric information problem, which is reflected in the trading spreads. As stock prices fluctuate, smaller firms are more vulnerable to liquidity; hence, the "flight-to-liquidity" phenomenon can be perceived as an extra source of volatility uncaptured by common pricing factors. Further, the puzzle disappears in the *Volume* model after considering the "flight-to-liquidity," contrary to the explanation of market friction. This indicates that the "flight-to-liquidity" more substantially explains the idiosyncratic volatility puzzle than market friction.[6]

Next, we discuss gambling behavior. The results from Panel A in Table 13 indicate that gambling behavior is more significant in

[5] The analyses for idiosyncratic volatility puzzle, gambling behavior, and momentum effects are only based on monthly data, referring to the previous studies (Ang et al., 2009; Boyer et al., 2007, 2010; Lu and Zhou, 2007). Idiosyncratic volatility (*Iv*) and idiosyncratic skewness (*Is*) are estimated by calculating the standard deviation and sample skewness of the daily residuals from Fama-French's three-factor model (Ang et al., 2009). We then sort the monthly cumulative returns for the momentum variable (*Mom*), as well the upper 30% of portfolio returns minus the lower 30%.

[6] We also examine the relationship between liquidity, return and realized volatility, and find that the relationships between liquidity measures and volatilities are significant, but the pricing factor of realized volatility is little affected by the flight-to-liquidity. These results will be given upon request.

Table 12
Estimations of Model (8) using monthly data with idiosyncratic volatility.

	*Esp**	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Without the interactions of firm (stock) size and illiquidity									
φ_7	−0.680***	−0.643***	−0.601***	−0.645***	−0.507***	−0.916***	0.266***	−0.144***	−0.312***
	(−17.94)	(−17.01)	(−15.89)	(−17.32)	(−16.42)	(−15.13)	(7.39)	(−3.55)	(−4.41)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.447	0.446	0.448	0.452	0.450	0.488	0.487	0.489	0.436
N	138,402	141,144	134,209	141,099	69,118	219,182	219,182	43,236	219,178
Panel B: With the interactions of firm size (stock) and illiquidity									
φ_4	−2.451***	−3.785***	−2.377***	−0.404***	−1.546***	1.693***	1.476***	3.380***	−2.030***
	(−6.84)	(−12.15)	(−8.87)	(−2.78)	(−8.70)	(6.79)	(17.27)	(30.17)	(−5.50)
φ_5	−1.446***	1.704**	−1.023***	0.649	1.683***	1.442***	−0.143	1.137***	−0.409
	(−2.72)	(2.13)	(−2.70)	(1.10)	(3.33)	(4.97)	(−0.61)	(4.67)	(−1.11)
φ_7	−0.074***	−0.069***	−0.077***	−0.070***	−0.505***	−0.917***	0.014	−0.022**	−0.318***
	(−3.89)	(−3.84)	(−3.90)	(−3.85)	(−16.46)	(−15.17)	(0.98)	(−2.16)	(−4.50)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
F-statistics	35.74	78.90	47.57	8.77	39.37	31.40	149.38	463.44	16.45
R^2	0.453	0.452	0.455	0.457	0.449	0.489	0.493	0.497	0.439
N	138,402	141,144	134,209	141,099	69,118	219,182	219,182	43,236	219,178

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are in parentheses, and the *F-statistics* are derived from the joint significance tests of φ_4 and φ_5. Robust standard errors are clustered at the firm (or stock) level.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 13
Estimations of Model (8) using monthly data with idiosyncratic skewness.

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Without the interactions of firm (stock) size and illiquidity									
φ_7	−0.080*	−0.063	−0.054	−0.084*	−0.166***	−0.233***	−0.041	−0.078**	−0.262***
	(−1.79)	(−1.40)	(−1.16)	(−1.88)	(−5.18)	(−4.64)	(−1.30)	(−2.48)	(−4.37)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.446	0.445	0.447	0.451	0.453	0.486	0.491	0.494	0.436
N	138,285	141,027	134,093	140,988	69,090	218,900	218,900	43,236	218,896
Panel B: With the interactions of firm (stock) size and illiquidity									
φ_4	−2.481***	−3.809***	−2.392***	−0.380***	−1.459***	1.695***	1.440***	3.327***	−1.990***
	(−6.94)	(−12.20)	(−8.93)	(−2.62)	(−8.40)	(6.95)	(17.12)	(31.11)	(−5.40)
φ_5	−1.571***	1.599*	−1.126***	0.529	1.387***	1.381***	0.005	1.277***	−0.429
	(−2.96)	(1.95)	(−2.97)	(0.90)	(2.84)	(4.80)	(0.02)	(5.65)	(−1.17)
φ_7	−0.072*	−0.057	−0.046	−0.079*	−0.160***	−0.233***	−0.028	−0.069**	−0.259***
	(−1.67)	(−1.32)	(−1.03)	(−1.82)	(−4.98)	(−4.65)	(−0.90)	(−2.24)	(−4.36)
Other Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month-Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
F-statistics	37.73	80.55	49.23	8.73	36.38	31.97	146.93	486.37	15.96
R^2	0.446	0.446	0.448	0.451	0.454	0.487	0.492	0.496	0.437
N	138,285	141,027	134,093	140,988	69,090	218,900	218,900	43,236	218,896

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are in parentheses, while the *F-statistics* are derived from the joint significance tests of φ_4 and φ_5. Robust standard errors are clustered at the firm (or stock) level.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

cases of indirect liquidity measures, including *Roll, Volume*, *Zeros, and Amihud*. Lottery-style stocks' prices are more inclined to experience large increase in the future, which compels investors to rush into such stocks; thus, their future prices should include the factor of idiosyncratic skewness. This phenomenon may relate to the firm size and level of liquidity. Panel B in Table 13, after

Table 14
Estimations of Model (8) using monthly data with momentum.

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Without the interactions of firm (stock) size and illiquidity									
φ_7	−0.016***	−0.017***	−0.016***	−0.017***	−0.007***	−0.020***	−0.005***	−0.010***	−0.015***
	(−16.59)	(−16.85)	(−16.55)	(−17.03)	(−8.11)	(−13.24)	(−5.31)	(−10.87)	(−7.46)
	0.448	0.447	0.449	0.453	0.451	0.491	0.489	0.492	0.438
Other Variables	yes	yes	Yes	yes	yes	yes	yes	yes	yes
R^2	yes	yes	Yes	yes	yes	yes	yes	yes	yes
N	140,883	143,710	136,648	143,661	67,736	216,312	216,312	42,835	216,308
Panel B: With the interactions of firm (stock) size and illiquidity									
φ_4	−2.379***	−3.199***	−2.291***	−0.330**	−1.646***	1.638***	1.505***	3.478***	−1.841***
	(−6.79)	(−7.98)	(−8.71)	(−2.29)	(−9.21)	(6.52)	(17.78)	(30.72)	(−4.97)
φ_5	−1.716***	0.731	−1.138***	0.386	1.762***	1.326***	−0.453*	0.884***	−0.352
	(−3.29)	(1.27)	(−3.03)	(0.66)	(3.44)	(4.57)	(−1.94)	(3.65)	(−0.95)
φ_7	−0.012***	−0.012***	−0.012***	−0.012***	−0.007***	−0.020***	−0.004***	−0.007***	−0.015***
	(−9.05)	(−8.88)	(−9.33)	(−9.08)	(−7.97)	(−13.09)	(−4.85)	(−7.71)	(−7.46)
Other Variables	yes	yes	Yes	yes	yes	yes	yes	yes	yes
F-statistics	38.12	32.24	47.13	7.53	43.83	28.17	159.53	478.04	13.36
R^2	0.448	0.447	0.450	0.453	0.451	0.492	0.490	0.495	0.438
N	140,883	143,710	136,648	143,661	67,736	216,312	216,312	42,835	216,308

Notes: All regressions are estimated by the FE (fixed-effects) model, which controls for the firm (or stock) fixed effects. The *t*-statistics are in parentheses, while the *F-statistics* are derived from the joint significance tests of φ_4 and φ_5. The robust standard errors are clustered at the firm (or stock) level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

controlling for the "flight-to-liquidity," notes that both the significances (see the *t*-statistics) and magnitudes of the coefficient φ_7 decrease in most columns. One possible reason is that smaller-sized stocks are more vulnerable to the trading volume, price impacts, and extra trading cost spread, which may deflate investors' "gold rush" to stocks with lottery-style prices. Our finding provides an alternative explanation regarding idiosyncratic skewness as a pricing factor; specifically, the "flight-to-liquidity" may partially account for the pricing factor.

Momentum is another significant market anomaly for most stock markets worldwide. Investors tend to herd in some stocks, regarded as momentum, similar to the "flight-to-liquidity" phenomenon. Therefore, if items for the "flight-to-liquidity" decrease the significance and magnitude of the coefficient's impact on the momentum factor, then we can infer that the "flight-to-liquidity" partially explains the momentum factor. Table 14 presents the related results; almost all models support our argument. Specifically, the models with high-frequency bid-ask spreads as illiquidity measures provide stronger evidence. Intuitively, under asymmetric information and transaction cost, part of private investors herd on some large firms, resulting in the "flight to liquidity" phenomenon. This finding indicates that momentum is not only observed as people's herding psychology, but also regarded as a rational investor behavior when facing asymmetric information and transaction costs.

7. Conclusion and implications

This paper uses panel data from China's stock market to provide new evidence for the proposition that illiquidity increases expected asset returns. We also consider various measures of stock illiquidity across time horizons: annually, monthly, and daily. Specifically, regarding the high-frequency bid-ask spreads as direct measures of illiquidity allows us to study the relationship between stock illiquidity and expected returns on the daily time horizon.

The results based on monthly data reveal that the expected stock illiquidity (or liquidity) has a positive (or negative) and significant effect on ex-ante excess stock returns, while the unexpected illiquidity (or liquidity) can negatively (or positively) and significantly affect contemporaneous stock returns. However, the estimations incorporating both annual and daily data, as well as the effects of unexpected illiquidity, more highly depend on the choice of illiquidity measures.

Further, the empirical analysis also suggests that the illiquidity's effects on excess stock returns vary across firm (or stock) size. Generally, the expected illiquidity's positive effects on excess returns are stronger for smaller firms, while the unanticipated illiquidity's negative effect on excess returns weakens as the firm size increases. Small stocks' large sensitivity toward illiquidity means that these stocks are subject to a greater illiquidity risk. If priced, such an event should result in a higher illiquidity risk premium. These results demonstrate that the purported "flight-to-liquidity" is partially explained by this liquidity's size effects. The inherent advantage of large firms and state-owned institutional backgrounds can account for this phenomenon.

Our study also notes that the results from using high frequency bid-ask spreads as illiquidity measures better support our main findings. This highlights the asymmetric information and transaction costs under an order-driven market structure and with a majority of private investors. Additionally, the “flight-to-liquidity” phenomenon still exists in most cases when considering market returns as a factor in influencing excess stock returns.

Finally, the “flight-to-liquidity” phenomenon can partially explain some frequent financial phenomena in China's stock market, including the idiosyncratic volatility puzzle, gambling behavior, and momentum.

Our study implies that the market participates in China's stock market—including regulators, policy-makers, and investors—should not ignore the “flight-to-liquidity” pricing factor. On the one hand, it highlights the weakness of some regulating policies that increase stock liquidity fluctuations, such as price limits and unexpected trading costs. Moreover, it also indicates the importance of alleviating information asymmetry. Introducing more market makers may improve the circumstances of the order-driven market. Additionally, introducing multiple strategic investors in state-owned firms may be also an effective measure to alleviate the liquidity constraints of the large state-owned firm. On the other hand, it is meaningful to manage the portfolio and arbitrage strategies. For example, traditional research tends to use momentum or gambling behavior to describe some stock price phenomena in a falling market. Actually, these phenomena more closely relate to the “flight-to-liquidity,” and this misunderstanding may induce inefficient portfolio management and losses in arbitrage.

Acknowledgments

This research is supported by research grants NSFC71301131 from National Natural Science Foundation of China and the Fundamental Research Funds for the Central Universities, JBK1801023.

Appendix A. Appendix

A.1. Summary statistics

Table A1
The descriptive statistics based on the annual data.*

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*	*Size*	*Re*	*Rmrf*
Panel A: Cross-section												
Mean	0.128	0.192	0.184	0.119	0.816	0.234	0.106	0.030	1.901	0.171	26	18
Sd	0.035	0.048	0.053	0.027	0.373	0.115	0.104	0.011	0.943	0.003	68	61
Esp	1											
Esp_c	0.867*	1										
Qsp	0.916*	0.901*	1									
Qsp_c	0.875*	0.991*	0.878*	1								
Roll	0.496*	0.414*	0.460*	0.461*	1							
Turnover	−0.162*	−0.279*	−0.030	−0.365*	0.131*	1						
Volume	−0.776*	−0.539*	−0.564*	−0.594*	−0.099*	0.641*	1					
Zeros	0.405*	0.599*	0.319*	0.641*	−0.173*	−0.684*	−0.546*	1				
Amihud	0.171*	−0.068*	0.148*	−0.076*	−0.123*	0.457*	−0.124*	−0.289*	1			
Size	−0.478*	−0.208*	−0.356*	−0.281*	−0.661*	−0.026	0.124*	0.076*	0.074*	1		
Re	−0.013	−0.122*	−0.008	−0.172*	−0.111*	0.825*	0.384*	−0.312*	0.546*	0.175*	1	
Rmrf	0.159*	0.067*	0.161*	0.016	−0.157*	0.734*	0.250*	−0.144*	0.533*	0.185*	0.973*	1
Panel B: Time-series												
Mean	0.129	0.193	0.185	0.117	0.816	0.234	0.106	0.030	1.901	0.171	26	18
Sd	0.229	0.055	0.146	0.096	0.288	0.090	0.173	0.012	0.701	0.002	13	3.5
Esp	1											
Esp_c	0.087*	1										
Qsp	0.070*	0.374*	1									
Qsp_c	0.010	0.563*	0.107*	1								
Roll	−0.004	−0.016	−0.009	−0.034*	1							
Turnover	0.026*	0.019	0.028*	0.034*	0.240*	1						
Volume	0.037*	0.026*	−0.009	0.106*	−0.084*	−0.019	1					
Zeros	0.085*	0.538*	0.231*	0.155*	−0.144*	−0.176*	0.437*	1				
Amihud	0.008	0.028*	0.001	−0.039*	0.086*	0.003	−0.026	0	1			
Size	0.031*	0.154*	0.070*	0.065*	0.144*	0.373*	0.099*	0.061*	0.030*	1		
Re	0.011	−0.148*	−0.077*	−0.084*	0.312*	0.063*	−0.038*	−0.197*	−0.028*	0.058*	1	
Rmrf	−0.004	−0.002	−0.031*	0.126*	0.052*	0.053*	0.071*	−0.094*	−0.011	0.005	0.252*	1

Notes: *Esp* and *Qsp* denote the time-weighted bid-ask spreads with trading and quotation, respectively. *Esp_c* and *Qsp_c* denote the closing bid-ask spreads with trading and quotation, respectively. *Turnover* denotes the turnover rate given by multiplying 10. *Volume* represents the trading volume given in 300 million. *Size* denotes the value of tradable stocks of a firm given in 100 billion. The Amihud illiquidity measure, *Amihud*, is given by multiplying 100. *Roll* is the value times 10. *Re* and *Rmrf* are the excessive stock return and excessive market return given by multiplying 100, respectively. Descriptions in Panel A refer to Famma-Fecbeth method, which takes the mean of variables across time series, and examines their cross-section correlation; while descriptions in panel B are generated by the opposite procedure. The sample period for the first four variables is from January 1, 2006, to September 30, 2015, and that for the remaining variables is from January 1, 2001 to September 30, 2015.

* $p < 0.01$

As shown in Table A1, the four bid-ask spread measures are highly positively correlated with each other. Additionally, the four bid-ask spread measures are positively correlated with Amihud illiquidity measure and *Zeros*, and negatively correlated with turnover rate and trading volume. In general, the time-series correlations for those variables are less significant than that of cross section. Direct illiquidity measures are less related to the turnover rate and Amihud illiquidity measure, but more correlated to the *Zeros* and trading volume.

Table A2
The descriptive statistics based on the monthly data.*

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Roll*	*Turnover*	*Volume*	*Zeros*	*Amihud*	*Size*	*Re*	*Rmrf*
Panel A: Cross-section												
Mean	0.131	0.194	0.186	0.121	0.112	0.228	0.104	0.030	0.966	0.200	1.43	0.785
Sd	0.054	0.057	0.074	0.033	0.059	0.136	0.114	0.014	0.520	0.002	9.78	8.709
Esp	1											
Esp_c	0.606*	1										
Qsp	0.530*	0.657*	1									
Qsp_c	0.628*	0.988*	0.648*	1								
Roll	0.1575*	0.1753*	0.2424*	0.1615*	1							
Turnover	−0.076*	−0.236*	−0.057*	−0.288*	0.2446*	1						
Volume	−0.426*	−0.443*	−0.394*	−0.463*	0.0137*	0.618*	1					
Zeros	0.233*	0.521*	0.245*	0.540*	−0.2078*	−0.609*	−0.493*	1				
Amihud	0.210*	0.188*	0.249*	0.177*	−0.104*	−0.155*	−0.349*	0.132*	1			
Size	0.094*	0.086*	0.042*	0.076*	0.277*	−0.009*	−0.012*	−0.041*	−0.048*	1		
Re	−0.115*	−0.134*	−0.087*	−0.167*	0.234*	0.470*	0.235*	−0.089*	−0.245*	0.111*	1	
Rmrf	−0.084*	−0.078*	−0.064*	−0.114*	0.161*	0.437*	0.204*	−0.032*	−0.187*	0.086*	0.9501	1
Panel B: Time-series												
Mean	0.132	0.195	0.188	0.117	0.112	0.228	0.103	0.030	0.966	0.200	1.43	0.785
Sd	0.165	0.056	0.139	0.097	0.016	0.074	0.164	0.012	0.392	0.000	0.87	0.228
Esp	1											
Esp_c	0.143*	1										
Qsp	0.094*	0.403*	1									
Qsp_c	0.034*	0.563*	0.115*	1								
Roll	0.0158*	−0.1585*	−0.1152*	−0.0346*	1							
Turnover	0.023*	0.021*	0.024*	0.026*	0.3187*	1						
Volume	0.044*	0.021*	−0.011*	0.102*	−0.0231*	−0.116*	1					
Zeros	0.130*	0.553*	0.247*	0.164*	−0.1723*	−0.214*	0.431*	1				
Amihud	0.021*	0.133*	0.055*	−0.028*	−0.123*	0.081*	−0.093*	0.013*	1			
Re	−0.000	−0.116*	−0.065*	−0.060*	0.038*	0.242*	−0.031*	−0.202*	0.047*	0.167*	1	
Rmrf	0.003	−0.019*	−0.034*	0.152*	0.098*	0.224*	0.058*	−0.114*	−0.054*	0.162*	0.231*	1

Notes: *Esp* and *Qsp* denote the time-weighted bid-ask spreads with trading and quotation, respectively. *Esp_c* and *Qsp_c* denote the closing bid-ask spreads with trading and quotation, respectively. *Turnover* denotes the turnover rate given by multiplying 10. *Volume* represents the trading volume given in 200 million. *Size* denotes the value of tradable stocks of a firm given in 10 billion. The Amihud illiquidity measure, *Amihud*, is given by multiplying 100. *Roll* is the value times 10. *Re* and *Rmrf* are the excessive stock return and excessive market return given by multiplying 100, respectively. Descriptions in Panel A refer to Famma-Fecbeth method, which takes the mean of variables across time series, and examines their cross-section correlation; while descriptions in panel B are generated by the opposite procedure. The sample period for the first four variables is from January 1, 2006, to September 30, 2015, and that for the remaining variables is from January 1, 2001, to September 30, 2015.

* $p < 0.01$.

For the monthly data in Table A2, the correlations between variables become weaker than those of annual data. Specifically, the four bid-ask spread measures are less positively correlated with each other, and almost all the cross-section correlations turn smaller, especially for indirect liquidity measures. In addition, *Zeros* still remains a weak correlation with direct liquidity measures as in the case of annual data.

Table A3
The descriptive statistics based on the daily data.*

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Turnover*	*Volume*	*Size*	*Re*	*Rmrf*
Panel A: Cross section									
Mean	0.197	0.191	0.192	0.173	0.221	0.103	0.105	0.075	0.040
Sd	0.059	0.061	0.062	0.057	0.145	0.122	0.081	2.020	1.797
Esp	1								
Esp_c	0.928*	1							
Qsp	0.992*	0.934*	1						
Qsp_c	0.920*	0.982*	0.934*	1					
Turnover	−0.164*	−0.256*	−0.233*	−0.303*	1				

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Table A3 (*continued*)

	Esp	*Esp_c*	*Qsp*	*Qsp_c*	*Turnover*	*Volume*	*Size*	*Re*	*Rmrf*
Volume	−0.433*	−0.412*	−0.488*	−0.477*	0.632*	1			
Size	−0.692*	−0.709*	−0.703*	−0.765*	0.471*	0.752*	1		
Re	−0.136*	−0.269*	−0.136*	−0.200*	0.139*	0.056*	0.043*	1	
Rmrf	−0.100*	−0.230*	−0.101*	−0.168*	0.125*	0.056*	0.023*	0.959*	1
Panel B: Time series									
Mean	0.198	0.192	0.194	0.174	0.221	0.103	0.105	0.075	0.040
Sd	0.051	0.056	0.054	0.052	0.071	0.165	0.572	0.046	0.015
Esp	1								
Esp_c	0.931*	1							
Qsp	0.984*	0.908*	1						
Qsp_c	0.957*	0.983*	0.926*	1					
Turnover	0.010*	0.009*	−0.014*	−0.028*	1				
Volume	−0.007*	0.039*	−0.053*	0.076*	−0.135*	1			
Size	−0.095*	−0.064*	−0.101*	−0.056*	−0.177*	0.510*	1		
Re	−0.135*	−0.131*	−0.118*	−0.161*	0.230*	−0.058*	−0.078*	1	
Rmrf	−0.047*	0.006*	−0.056*	−0.017*	0.163*	0.056*	0.037*	0.036*	1

Notes: *Esp* and *Qsp* denote the time-weighted bid-ask spreads with trading and quotation, respectively. *Esp_c* and *Qsp_c* denote the closing bid-ask spreads with trading and quotation, respectively. *Turnover* denotes the turnover rate given by multiplying 10. *Volume* represents the trading volume given in 100 million. *Size* denotes the value of tradable stocks of a firm given in 10 billion. *Re* and *Rmrf* are the excessive stock return and excessive market return given by multiplying 100, respectively. Descriptions in Panel A refer to Famma-Fecbeth method, which takes the mean of variables across time series, and examines their cross-section correlation; while descriptions in panel B are generated by the opposite procedure. The sample period for the first four variables is from January 1, 2006, to September 30, 2015, and that for the remaining variables is from January 1, 2001 to September 30, 2015.

* $p < 0.01$.

As for the daily data in Table A3, the direct illiquidity measures have strong correlations with each other on both cross-section and time-series dimensions. In addition, the correlations for indirect illiquidity measures are similar to those of monthly data in the cross-section level, but become smaller in the time-series level.

Above tables also show that all of the illiquidity measures, firm size, and market excessive are closely correlated to the stock excess return. These stylized facts suggest the importance of considering illiquidity, size, and market risk in asset pricing model.

A.2. Description based on intraday data of some firms

The following figures give a general knowledge of the phenomenon "flight-to-liquidity" based on the intraday data of some firms. We mainly provide three variables -price, trading volume, and bid-ask spread -tick to tick. Corresponding to the Fig. 1, we choose two firms with the large size and another two firms with the small size, and compare these two groups in May 30, 2007 and February 27, 2007, respectively.

From Fig. A1, we notice that in May 30, 2007, the price of Hua Neng Power International (HNPI) dropped 5.39% from 14.65 to 13.86. During this day, its prices in some time intervals are almost constant, along with the low trading volume and almost constant bid-ask spread. Due to its large size (114.27 billion RMB), the price of this firm in that day did not touch the price limit (−10%). However, the situation is more serious for the stock Meili Cloud (MLC) shown in Fig. A3. Its price dropped 10% from 18.10 to 16.29. Due to the price limit rule, the liquidity of this smaller firm (2.58 billion RMB) almost disappeared after 11 p.m. in that day. In February 27, 2007, we witnessed the similar tends for another two firms Beijing North Star (BJNS) and Go Sun (GS) in Figs. A2 and A4, respectively.

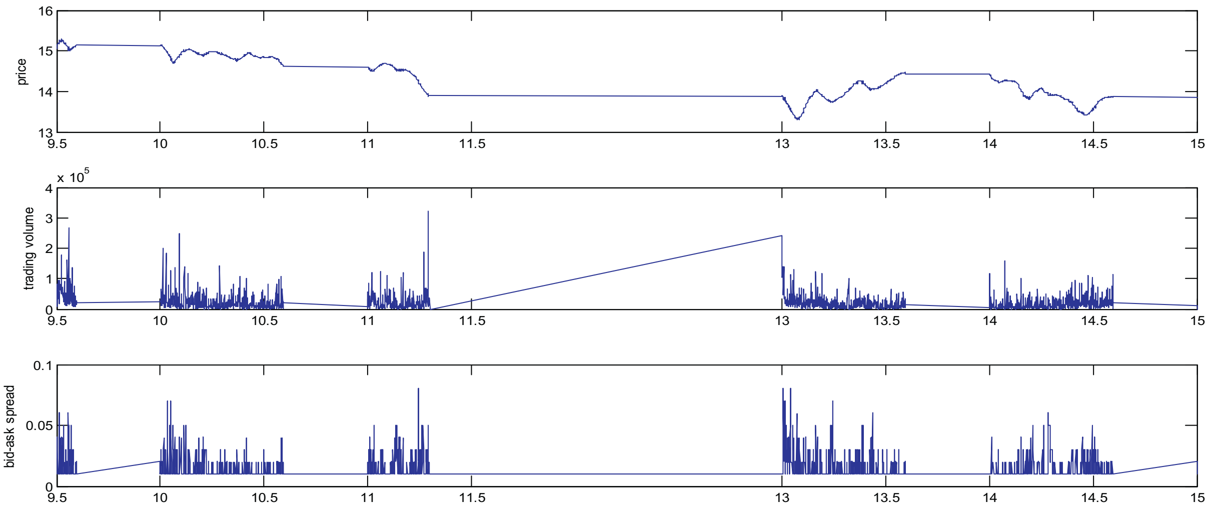

Fig. A1. The description of high-frequency data of the stock Hua Neng Power International (trading code, 600011) in May 30, 2007.
Note: The horizontal line depicts the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. The data is drawn with tick to tick. The bid-ask spread is calculated by the ask price minus bid price. The trading volume is in million RMB per unit.

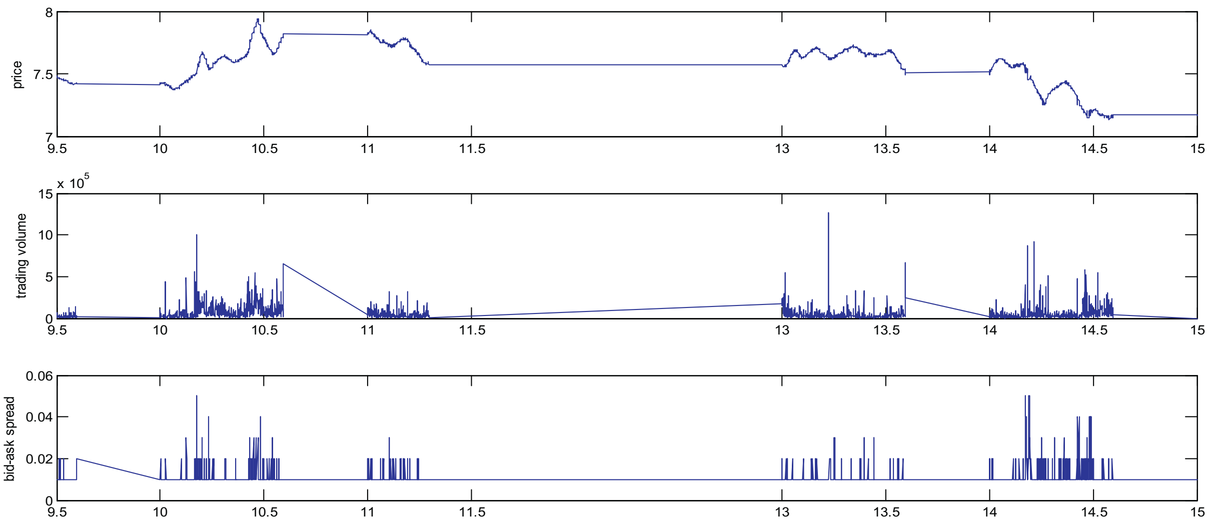

Fig. A2. The description of high-frequency data of the stock Beijing North Star (trading code, 601588) in February 27, 2007.
Note: The horizontal line depicts the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. The data is drawn with tick to tick. The bid-ask spread is calculated by the ask price minus bid price. The trading volume is in million RMB per unit.

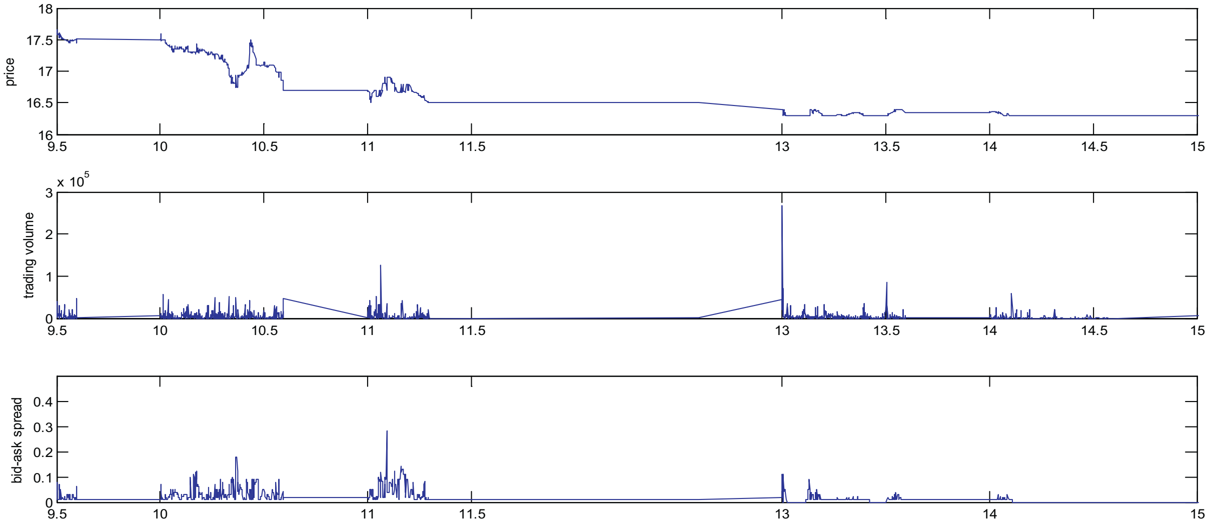

Fig. A3. The description of high-frequency data of the stock Meili Cloud (trading code, 000815) in May 30, 2007.
Note: The horizontal line depicts the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. The data is drawn with tick to tick. The bid-ask spread is calculated by the ask price minus bid price. The trading volume is in million RMB per unit. Since the price limit is touched after 14:00, there was no trade happened, and the bid-ask spread was zero. In the third subplot, we make bid-ask spread equal to zero for easier drawing the figure.

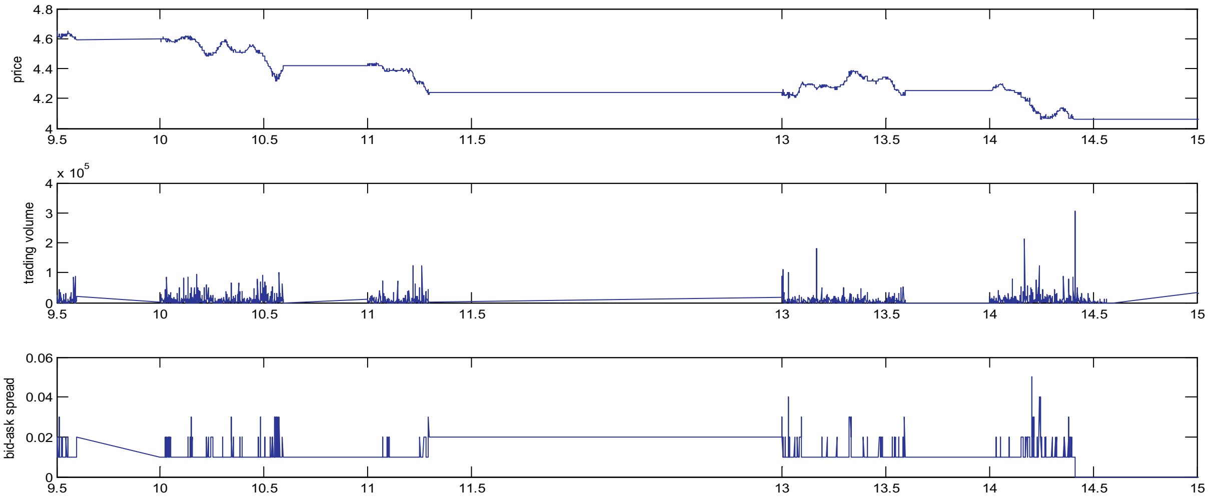

Fig. A4. The description of high-frequency data of the stock Go Sun (trading code, 000971) in February 27, 2007.
Note: The horizontal line depicts the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. The data is drawn with tick to tick. The bid-ask spread is calculated by the ask price minus bid price. The trading volume is in million RMB per unit. Since the price limit is touched after 14:00, there was no trade happened, and the bid-ask spread was zero. In the third subplot, we make bid-ask spread equal to zero for easier drawing the figure.

To make it easier to interpret the intraday data, we also provide the descriptive statistics in Table A4 as an example. The descriptive statistics are calculated based on the one month high-frequency data of stock Meili Cloud (trading code, 000815) in Feburary 2007. All the data comes from the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. If the price limit rule is touched, then the observations of Bid-ask spread are zeros, which means no trade happens.

Table A4
The descriptive statistics of the stock Meili Cloud (trading code, 000815) in February, 2007.

	Mean	Max	Min	Std	Skewness	Kurtosis
Bid-ask spread	0.857	14.51	0	3.083	3.430	12.828
Price	11.394	14.51	8.3	1.939	−0.147	1.487
Volume	3900.850	614,970	0	13,970.486	17.799	

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Table A4 (*continued*)

	Mean	Max	Min	Std	Skewness	Kurtosis
						531.355

Note: all the data comes from the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. The descriptive statistics are calculated tick-by-tick based on the one-month high-frequency data. If the price limit rule is touched, then the observations of bid-ask spreads are zeros, which means no trade happens.

A.3. Descriptive statistics across whole sample with different sampling frequency of intraday data

Tables A5–A8 reports the descriptive statistics of the *Bid-ask spread*, *Price* and *Volume* with 5, 15, 30, and 60 min, respectively. As mentioned in Table A4, the firm faces serious illiquidity in the month of February, 2007. However, comparing with one-month analysis of a firm, the whole sample analysis shows that the stocks with more liquid have lower average bid-ask spread and large average trading volume in high-frequency trading.

Table A5
Descriptive statistics of the China's A stocks from 2006 to 2015 based on 5 min sampling.

	Mean	Max	Min	Std	Skewness	Kurtosis
Bid-ask spread	0.212	18.970	0	0.461	11.691	313.357
Price	10.898	193.541	0.194	9.266	4.913	54.772
Volume	6657.374	194,554	0	6397.419	8.457	141.906

Note: all the data comes from the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. If the price limit rule is touched, then the observations of bid-ask spreads are zeros, which means no trade happens.

Table A6
Descriptive statistics of the China's A stocks from 2006 to 2015 based on 15 min sampling.

	Mean	Max	Min	Std	Skewness	Kurtosis
Bid-ask spread	0.213	18.636	0	0.461	11.399	295.651
Price	10.898	193.827	0.193	9.267	4.914	54.800
Volume	6647.286	190,171	0	6391.066	8.334	136.186

Note: all the data comes from the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. If the price limit rule is touched, then the observations of bid-ask spreads are zeros, which means no trade happens.

Table A7
Descriptive statistics of the China's A stocks from 2006 to 2015 based on 30 min sampling.

	Mean	Max	Min	Std	Skewness	Kurtosis
Bid-ask spread	0.214	18.724	0	0.463	11.373	295.525
Price	10.898	193.838	0.193	9.267	4.914	54.809
Volume	6652.426	184,161	0	6340.293	8.020	126.067

Note: all the data comes from the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. If the price limit rule is touched, then the observations of bid-ask spreads are zeros, which means no trade happens.

Table A8
Descriptive statistics of the China's A stocks from 2006 to 2015 based on 1 h sampling.

	Mean	Max	Min	Std	Skewness	Kurtosis
Bid-ask spread	0.214	18.420	0	0.464	11.151	281.153
Price	10.898	193.879	0.193	9.267	4.915	54.824
Volume	6693.641	239,239	0	6673.009	9.661	202.563

Note: all the data comes from the trading time of each day from 9:30 to 11:30 and 13:00 to 15:00. If the price limit rule is touched, then the observations of bid-ask spreads are zeros, which means no trade happens.

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