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Pricing of liquidity risks: Evidence from multiple liquidity measures☆

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ABSTRACT

We investigate the pricing implication of liquidity risks in the liquidity-adjusted capital asset pricing model of Acharya and Pedersen (2005), using multiple liquidity measures and their principal component. While we find that the empirical results are sensitive to the liquidity measure used in the test, we find strong evidence of pricing of liquidity risks when we estimate liquidity risks based on the first principal component across eight measures of liquidity, both in the cross-sectional and factor-model regressions. Our finding implies that the systematic component measured by each liquidity proxy is correlated across measures and the shocks to the systematic and common component of liquidity are an undiversifiable source of risk.

1. Introduction

Liquidity proxies measure systematic liquidity, but not without noise. Hence, the quality of liquidity proxies, or the extent to which it measures systematic components of liquidity, plays an important role in the research of asset pricing with liquidity risk. Furthermore, the systematic component of measured liquidity may be driven by either a systematic and common component that is simultaneously captured by different measures of liquidity, or a systematic but measure-specific component of liquidity. That is, each measure could be either a noisy proxy for the same dimension of liquidity or a proxy for the different dimension of liquidity. Given the limitation of a single liquidity measure, this paper investigates the pricing of liquidity risks by multiple measures of liquidity. Specifically, we test the liquidity-adjusted capital asset pricing model (LCAPM) of Acharya and Pedersen (2005) in the US stock market during 1962–2011, using eight different measures of liquidity. Employing multiple measures of liquidity enables us to examine whether the pricing of liquidity risks is specific to the measure used in the test. Moreover, based on multiple measures of liquidity, we can now investigate the pricing implication of liquidity risks when liquidity risks are estimated from a systematic and common component across different liquidity measures. To the best of our knowledge, this is the first study to investigate the pricing of multiple sources of systematic liquidity risks as specified in the LCAPM using multiple liquidity proxies as well as their principal component.

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We evaluate the LCAPM because it provides a unified framework to examine the effect of liquidity on asset returns by encompassing various channels in one model through which liquidity affects asset prices. Specifically, other than the covariance of stock return with market return in the traditional capital asset pricing model (CAPM), the LCAPM includes three additional covariances that are related to stock or market *liquidity*—covariance of stock liquidity with market liquidity, covariance of stock liquidity with market return, and the covariance of stock return with market liquidity. Most importantly, the LCAPM theoretically motivates that the pricing of liquidity risks is independent of the pricing of market risk, as specified in the traditional capital asset pricing model. Previous studies in asset pricing with liquidity mostly have focused on the pricing of liquidity as a stock characteristic (Amihud, 2002; Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996) or as a covariance risk based on stock *return* and market *liquidity* (Korajczyk and Sadka, 2008; Liu, 2006; Pástor and Stambaugh, 2003; Sadka, 2006). In addition to these two sources of pricing of liquidity, the LCAPM proposes two more channels, which arise from the covariance of stock *liquidity* with market *liquidity* ("commonality in liquidity") and that of stock *liquidity* with market *return*. Although a group of research shows that shocks to liquidity are a systematic source of risk by presenting the existence of commonality in liquidity (Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Karolyi et al., 2012), its pricing implication is first theoretically modeled in the LCAPM.[1]

Most of the aforementioned empirical studies employ one single liquidity measure. For example, Acharya and Pedersen (2005) borrow the measure from Amihud (2002), and Pástor and Stambaugh (2003), Liu (2006), and Sadka (2006) respectively propose new measures for their studies. Recently, Lee (2011) empirically tests the LCAPM on a global level using stocks from 50 countries, but he also uses only one liquidity measure. The limitation of using one single measure is clear, as shown by Hasbrouck (2005), and Goyenko et al. (2009), all of whom find that the quality of liquidity measures varies. More importantly, empirical results based on a single measure raise the issue of whether the results are driven by systematic but *measure-specific* components or by systematic and *common* components of measured liquidity. That is, if each measure evaluates different dimension of liquidity, the empirical results showing the significant pricing of liquidity risk may suggest the existence of multiple premia for each different aspect of measured liquidity. On the contrary, when each measure evaluates systematic and common component across measures, the significant pricing of liquidity may imply the existence of a single premium for common liquidity. We therefore ask the following important questions: Does the pricing of liquidity risks vary according to the measures used in the test? If so, why do some measures show supporting evidence of pricing of liquidity risks, while others do not? Is it because of the difference in each measure's level of goodness in capturing the systematic and common component, or is it because each measure proxies a different aspect of liquidity? Can we find evidence of the pricing of liquidity that is common across different measures?

Focusing on this issue, Korajczyk and Sadka (2008) find the existence of a common component across eight measures of liquidity in a principal component analysis (PCA) framework. They further show that this systematic common component is accompanied by a significant liquidity premium, while the measure-specific liquidity that is orthogonal to the common component is not. However, the channel of pricing of liquidity in their study is restricted only to the level of liquidity and the covariance of stock *return* with market *liquidity*, leaving room for further research on the pricing of commonality in liquidity and the covariance of stock liquidity with market return. That is, in addition to the test of the pricing implication of liquidity shown in Korajczyk and Sadka (2008), we also test in this paper whether the commonality in liquidity is related to stock returns in a way that stocks whose liquidity improves when the market liquidity dries up are traded at a premium, as modeled in the LCAPM. Moreover, the LCAPM shows that the covariance of stock liquidity (illiquidity) with market return are positively (negatively) related to stock returns, implying that stocks that are difficult to sell in a down market are traded at a discount.[2] This pricing implication is also motivated by Kyle and Xiong (2001), Morris and Shin (2004), and Brunnermeier and Pedersen (2009), who show that arbitrageurs demand compensation for bearing liquidity risk when they are forced to liquidate their positions facing large market declines. Overall, by testing the LCAPM using alternative measures of liquidity, our paper extends Korajczyk and Sadka (2008) to the pricing of multiple liquidity risks which are theoretically encompassed in an asset pricing model.

Given the limitation of each liquidity measure, we use eight different measures of liquidity and examine whether the empirical result of pricing of liquidity risks vary depending on the measure. Specifically, we use price impact measures introduced by Amihud (2002) and Pástor and Stambaugh (2003), zero-return based-measures by Lesmond et al. (1999) and Liu (2006), serial correlation-based measure of Roll (1984), price-based spread proxy of Corwin and Schultz (2012), and effective tick measure of Goyenko et al. (2009).[3] The correlations among liquidity measures range from -0.23 to 0.87 and are positive and highly significant in the Pearson correlation tests in most cases. In addition, time-series plots of shocks in market-wide liquidity show that the anecdotal events of dried-up liquidity are jointly and successfully indicated by different measures. However, our cross-sectional regression tests indeed show that the empirical results provide only weak evidence of pricing of liquidity and are rather sensitive to the liquidity measure used in the test. All these imply that our liquidity proxies measure the systematic and common component of liquidity, but not without negligible level of noises. Hence, we extract systematic and common aspects of liquidity across different measures by principal components analysis to investigate whether liquidity risks based on this systematic and common component of liquidity are priced in the US market. Consistent with Korajczyk and Sadka (2008), we find

[1] Bekaert et al. (2007) empirically test pricing of multiple liquidity risks. However, the pricing implication of these liquidity risks is theoretically modeled by Acharya and Pedersen (2005).

[2] "Whenever the market turns against you, you take the biggest losses in illiquid securities," says Richard Bookstaber, former head of risk management at Salomon Bros. "Because there are so few buyers, you're forced to sell at a discount that is both huge and highly unpredictable" (p.49, Fortune, November26, 2007; recited from Lee (2011)).

[3] We focus on the liquidity measures based on return and trading volume since they are popular, easy to compute, and provide longer time-series. By the same reason, we exclude measures based on intra-daily data (such as TAQ database).

that about 33% of the whole variation in liquidity proxies is explained by the first principal component across different measures, which implies the existence of systematic and common components in measured liquidity.

In subsequent asset pricing tests both in the cross-sectional and factor-model regressions, we estimate liquidity risks based on the first principal component across measures of liquidity for a given stock. By focusing on the first principal component, we bear the risk of losing information which is contained in a specific measure that is not common across measures. However, principal component-based tests enable us to examine whether it is the common or the measure-specific component that is being priced. Consistent with Korajczyk and Sadka (2008), we indeed find strong evidence of pricing of the systematic and common component of liquidity. This finding, together with the weak pricing results based on a single liquidity measure, implies that it is the common underlying factor in measured liquidity that carries a significant premium.

The tests based on PCA show that the liquidity risks based on the covariance of stock *liquidity* with market return and market liquidity are significantly priced in a way that a stock's required rate of return increases with the stock's degree of commonality in liquidity as well as with the degree of difficulty in selling the stock in a market downturn. In portfolio management, the findings of this paper imply that investors need to consider how easy it will be to liquidate shares not just in a down market but also in a market with dried-up liquidity. This challenges the traditional asset pricing framework of Merton (1973), who argues that it is a stock *return* whose covariance with market variable is incorporated into the priced state variable. Overall, our result suggests that the systematic and common aspects of liquidity that each noisy liquidity proxy jointly measures provide evidence in support of the LCAPM, implying that liquidity is a source of undiversifiable risk that is independent from the traditional market risk.

This paper is organized as follows. Section 2 briefly introduces Acharya and Pedersen's (2005) LCAPM. Data and liquidity proxies are illustrated in Section 3 and estimation of liquidity risks is presented in Section 4. Empirical results are summarized in Section 5 and we conclude in Section 6.

2. Liquidity-adjusted capital asset pricing model

Acharya and Pedersen (2005) derive the LCAPM in a traditional framework, in that risk-averse investors maximize their expected utility under a wealth constraint. The authors extend the assumption of perfect capital markets without trading costs to a world where stochastic trading costs exist. Specifically, in an overlapping-generations economy, the trading cost-free stock price is replaced with the *stochastic trading-cost-adjusted* stock price and the LCAPM is presented as

$$E_t\left(R_{i,t+1}-C_{i,t+1}\right) = R_f + \lambda_t \frac{Cov_t\left(R_{i,t+1}-C_{i,t+1}, R_{M,t+1}-C_{M,t+1}\right)}{Var_t\left(R_{M,t+1}-C_{M,t+1}\right)}. \tag{1}$$

where R_i is the return of stock i, R_M is market return, R_f is a risk-free rate (all returns in gross terms), and $C_{i,t}$ is a trading cost per price at time t. The subscript t in the operators denotes that these operators are conditional on the information set available up to time t. As a result of incorporating stochastic liquidity, the LCAPM has three covariance terms related to trading costs in addition to the traditional market risk. When the trading cost terms are zero, the LCAPM in Eq. (1) is collapsed to the traditional capital asset pricing model.

The unconditional version of the LCAPM is derived by assuming constant conditional variances or constant premiums and is specified as

$$E_t\left(R_{i,t}-R_{f,t}\right) = E\left(C_{i,t}\right) + \lambda\beta_i^1 + \lambda\beta_i^2 - \lambda\beta_i^3 - \lambda\beta_i^4, \tag{2}$$

where

$$\begin{aligned}
\beta_i^1 &= \frac{Cov\left(R_{i,t}, R_{M,t}\right)}{Var\left(R_{M,t}-\left[C_{M,t}-E_{t-1}\left(C_{M,t}\right)\right]\right)}, \\
\beta_i^2 &= \frac{Cov\left(C_{i,t}-E_{t-1}\left(C_{i,t}\right), C_{M,t}-E_{t-1}\left(C_{M,t}\right)\right)}{Var\left(R_{M,t}-\left[C_{M,t}-E_{t-1}\left(C_{M,t}\right)\right]\right)}, \\
\beta_i^3 &= \frac{Cov\left(R_{i,t}, C_{M,t}-E_{t-1}\left(C_{M,t}\right)\right)}{Var\left(R_{M,t}-\left[C_{M,t}-E_{t-1}\left(C_{M,t}\right)\right]\right)}, \\
\beta_i^4 &= \frac{Cov\left(C_{i,t}-E_{t-1}\left(C_{i,t}\right), R_{M,t}\right)}{Var\left(R_{M,t}-\left[C_{M,t}-E_{t-1}\left(C_{M,t}\right)\right]\right)}.
\end{aligned} \tag{3}$$

The risk premium is defined as $\lambda = E\ (\lambda_t) = E(R_{M,t} - C_{M,t} - R_{f,t})$ in Eq. (2). Since liquidity is persistent (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Korajczyk and Sadka, 2008), trading cost terms are denoted in terms of their innovation.

We define the liquidity net beta, β_i^5, as a linear combination of the three liquidity betas in Eq. (4) to distinguish the pricing effect of liquidity risks from that of market risk[4]:

$$\beta_i^5 \equiv \beta_i^2 - \beta_i^3 - \beta_i^4. \tag{4}$$

The economic interpretation of each beta is as follows: β_i^1 denotes the traditional market beta as in the CAPM, adjusted for terms related to trading cost in the denominator. β_i^2 is liquidity risk arising from the comovement of stock illiquidity with market illiquidity. The pricing implication of this risk is first theoretically modeled in the LCAPM and the model shows that it is positively related to asset returns, reflecting the positive compensation for investors for holding a stock whose illiquidity increases when market illiquidity is high. We refer to this liquidity risk as commonality beta throughout the paper. β_i^3 captures the covariance risk of a stock return and the market illiquidity and is shown to be negatively related to expected return, reflecting investors' willingness to accept a lower expected return on a security whose return tends to be high when the market is illiquid. In the model, the covariance of stock illiquidity with market return, β_i^4, is shown to be negatively related to expected return, since investors are willing to accept a lower expected return on a security that has a lower stochastic trading cost in a down market.

3. Data and illiquidity measures

3.1. Data screening

We collect the daily return, price, and trading volume data of common shares for non-financial firms listed in the New York Stock Exchange and the American Stock Exchange from CRSP daily stock files for July 1, 1962, to December 31, 2011. Monthly returns and prices are collected from CRSP monthly stock files for the corresponding period. We apply the data screening procedure similar to that in the previous studies in liquidity (e.g., Chordia et al. (2000), Pástor and Stambaugh (2003), and Huang (2005)). To be included in the sample, stocks are required to have at least 100 positive trading volume days over the sample period. To prevent any disruptive influence from extremely large or small stocks, if any of the previous year-end stock price is less than or equal to \$5 or greater than or equal to \$1,000, that stock is dropped from the sample for that year. If a stock shifts its trading venue in any given year, that stock is also dropped from the sample for that year. Since stock splits affect liquidity (Conroy et al., 1990; Schultz, 2000; Dennis and Strickland, 2003; Gray et al., 2003; Goyenko et al., 2005), we exclude stocks for the year when the splits occur. We also drop observations for stocks that are delisted (CRSP distribution codes beginning with 5) from the year when the delisting occurs. Stocks are also required to have non-negative market capitalization and book-to-market ratios to be included in the sample. In building the monthly measure of illiquidity, stocks are required to have at least 15 valid daily observations in a given month.[5] At the last step, we restrict the sample stocks to those having all eight monthly illiquidity measures, which are going to be introduced in the next section. After all this screening process, we have a total of 4940 stocks in the sample.

3.2. Illiquidity measures

Since the LCAPM specifies illiquidity rather than liquidity, we use the following eight measures as proxies for illiquidity. Our first illiquidity measure is a price impact measure of Amihud (2002):

$$RV_{i,d,t} \equiv \frac{|r_{i,d,t}|}{P_{i,d,t} \cdot VO_{i,d,t}} \times 10^6, \tag{5}$$

where $P_{i,d,t}$ and $VO_{i,d,t}$ are the price and daily share trading volume (in one share unit) of stock i on day d in month t, respectively. Note that this measure is defined only for positive trading volume days. The monthly illiquidity measure is constructed as an equally weighted average of daily RVs in a given month.

We use the reversal measure of illiquidity from Pástor and Stambaugh (2003), which is estimated from:

$$r_{i,d+1,t} - r_{M,d+1,t} = \alpha_{i,t} + \beta_{i,t} r_{i,d,t} + \gamma_{i,t} sign\left(r_{i,d,t} - r_{M,d,t}\right) \cdot dvol_{i,d,t} + \varepsilon_{i,d,t}, \tag{6}$$

where $r_{i,d,t}$ is the return of stock i on day d in month t, $r_{M,d,t}$ is the market return (CRSP value-weighted index return) on day d in month t, and $dvol_{i,d,t}$ is the dollar trading volume (in million-dollar unit). The coefficient of the signed dollar trading volume, $\gamma_{i,t}$, is a liquidity measure and is expected to be negative, reflecting price reversals due to a large trading volume. To convert it to an illiquidity measure, we multiply it by -1 and obtain the illiquidity measure, PS:

$$PS_{i,t} \equiv \gamma_{i,t} \times (-1). \tag{7}$$

[4] By defining "net beta" as $\beta_i^{net} = \beta_i^1 + \beta_i^2 - \beta_i^3 - \beta_i^4$, Acharya and Pedersen (2005) tested $R_i - R_f = a + bC_i + \lambda_1\beta_i^1 + \lambda_5\beta_i^{net} + \epsilon_i = a + bC_i + (\lambda_1 + \lambda_5)\beta_i^1 + \lambda_5(\beta_i^2 - \beta_i^3 - \beta_i^4) + \epsilon_i$. Note that λ_5 is a premium for liquidity risks and, at the same time, the part of market risk premium in this specification. By defining liquidity net beta by excluding β_i^1, we test $R_i - R_f = a' + b'C_i + \lambda_1'\beta_i + \lambda_5'\beta_i^5 + \epsilon_i' = a' + b'C_i + \lambda_1'\beta_i^1 + \lambda_5'(\beta_i^2 - \beta_i^3 - \beta_i^4) + \epsilon_i'$. This specification enables us to distinguish the pricing effect of liquidity risks, λ_5', and the pricing effect of market risk, λ_1'.

[5] For September 2001, stocks are required to have at least 14 daily observations because the number of trading days in this month is 15 due to the stock market closing by the 9/11 terrorist attack.

When the trading cost is too high to cover the benefit from informed trading, informed investors would choose not to trade and this non-trading should lead to an observed zero return for that day. Based on this intuition, Lesmond et al. (1999) propose the zero-return proportion measure of illiquidity which is computed as:

$$ZR_{i,t} = N_{i,t}/T_t, \tag{8}$$

where T_t is the number of trading days in month t and $N_{i,t}$ is the number of zero-return days of stock i in month t.

One potential caveat of ZR is that it may produce the same level of illiquidity for multiple stocks for multiple periods. To overcome this potential problem, Liu (2006) proposes a turnover-adjusted zero-return measure,

$$LMx_{i,t} = \left[N_Z + \frac{1/TVx}{DF}\right] \times \frac{21x}{N_x}, \tag{9}$$

where N_Z is the number of zero-volume days in the previous x months; TVx is turnover over the previous x months, which is computed as the sum of daily trading volume divided by the number of shares outstanding; N_x is the total number of trading days over the previous x months; and DF is a deflator that constrains, for all sample stocks, the second term in the square brackets of Eq. (9) to be within the boundary of zero and one (not inclusive). Following Liu (2006), we use 11,000, which satisfies the boundary condition for DF for our sample. The last term in Eq. (9) is used to adjust the measure to be comparable to other monthly measures. We use $LM12$, which is based on the previous 12 months' data.

Lesmond et al. (1999) propose a measure of stochastic trading cost based on the intuition that trading costs are reflected in observed stock returns if the informed arbitrageurs trade only when the returns in excess of market returns exceed the threshold level of trading costs. According to their limited dependent variable model of returns, the observed returns, R_{jt}, are modeled as below, under the assumption that the true, unobserved returns, R^*_{jt}, are given by the market model

$$R^*_{jt} = \beta_j R_{mt} + \varepsilon_{jt}, \tag{10}$$

where,

$$\begin{aligned} R_{jt} &= R^*_{jt} - \alpha_{ij}, \text{ if } R^*_{jt} < \alpha_{1j}, \\ R_{jt} &= 0, \text{ if } \alpha_{1j} < R^*_{jt} < \alpha_{2j}, \\ R_{jt} &= R^*_{jt} - \alpha_{2j}, \text{ if } R^*_{jt} > \alpha_{2j}. \end{aligned} \tag{11}$$

The parameter estimates are obtained through maximum likelihood estimation. α_{1j}, which is restricted to be negative, is the sell-side trading cost, while α_{2j}, restricted to be positive, is the buy-side trading cost. The measure of the proportional round-trip trading cost, LOT, is defined as the difference between the two, $\alpha_{2j} - \alpha_{1j}$.

In a recently published paper, Corwin and Schultz (2012) develop a bid–ask spread estimator from the ratio of daily high and low prices by separating out the volatility component from it. The daily high and low price ratio can be viewed as bid–ask spread because daily high (low) prices are almost always buy (sell) trade. To separate out the volatility component from the price ratio, the authors use the fact that the variance increases proportionally with return interval, while spread does not. The closed form solution for their spread estimator is:

$$S = \frac{2\left(e^K - 1\right)}{1 + e^K} \tag{12}$$

$$K = \left(\sqrt{2E\left\{\sum_{j=0}^{1}\left[\ln\left(P^H_{t+j}/P^L_{t+j}\right)\right]^2\right\}} - \sqrt{E\left\{\sum_{j=0}^{1}\left[\ln\left(P^H_{t+j}/P^L_{t+j}\right)\right]^2\right\}}\right) / \left(3-2\sqrt{2}\right) - \sqrt{\left[\ln\left(P^H_{t,t+1}/P^L_{t,t+1}\right)\right]^2 / \left(3-2\sqrt{2}\right)}, \tag{13}$$

where P^H_t and P^L_t are the observed high and low stock price at day t, respectively. We construct a monthly measure, CS, by computing the average of daily estimated spread S in a given month.

Roll (1984) proposes a proxy for effective spread based on bid–ask bounce: $2\sqrt{-Cov(r_{i,d}, r_{i,d-1,t})}$. In the case of positive covariance, we force covariance terms to have negative values by taking absolute values with a negative sign added (Harris, 1989; Lesmond, 2005). Thus, Roll's measure is defined as

$$RO_{i,t} = 2\sqrt{\left|Cov\left(r_{i,d}, r_{i,d-1,t}\right)\right|}. \tag{14}$$

The last measure that we employ is the effective tick (ET) measure from Goyenko et al. (2009). ET is a proxy of the effective spread obtained from clustered trade prices. It is computed as:

$$\text{Effective Tick}(ET) = \frac{\sum_{j=1}^{J} \hat{\gamma}_j s_j}{\overline{P_k}}. \tag{15}$$

Following Hagströmer et al. (2011), we obtain s_j by the 1/8 price grid (in which the possible spreads are at \$1/8, \$1/4, \$1/2, and \$1) before July 1997, by the 1/16 price grid (in which the possible spreads are at \$1/16, \$1/8, \$1/4, \$1/2, and \$1) from July 1997 to January 2001, and by the decimal grid (in which the possible spreads are at \$0.01, \$0.05, \$0.1, \$0.25, and \$1) after January 2001. $\overline{P_k}$ is the average of daily prices in month k, and $\hat{\gamma}_j$ is defined as

$$\hat{\gamma}_j = \begin{cases} \mathrm{Min}\left[\mathrm{Max}\left\{U_j, 0\right\}, 1\right], & j = 1 \\ \mathrm{Min}\left[\mathrm{Max}\left\{U_j, 0\right\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k\right], & j = 2, 3, \ldots, J \end{cases} \tag{16}$$

based on

$$U_j = \begin{cases} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \ldots J-1 \\ F_j - F_{j-1}, & j = J \end{cases} \tag{17}$$

$$F_j = \frac{N_j}{\sum_{j=1}^{J} N_j} \text{ for } j = 1, 2, \ldots, J. \tag{18}$$

N_j is the number of trades on prices corresponding to the jth spread using positive volume days.

Similar to Amihud (2002) and Lesmond (2005), we winsorize the measures with a lower bound, e.g., *RV*, *ZR*, *LM12*, *LOT*, *RO*, and *ET* at the top 1% and *PS* and *CS* at the top and bottom 1%.

4. Estimation of betas

In this section, we estimate liquidity risks based on the illiquidity measures introduced earlier. Since investors request a premium for bearing liquidity only when the liquidity shock is systematic and persistent (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Korajczyk and Sadka, 2008), we begin this section by constructing market aggregate illiquidity and investigating the persistence of it.

4.1. Market aggregate illiquidity

Table 1 shows the average monthly percentage returns, illiquidity, and other stock characteristics for 25 equally-weighted size portfolios, which are annually rebalanced based on the total market value of each stock at the end of the previous year. In the last column of the table, we report the average number of stocks for each size portfolio. Since it is well known that illiquidity is higher for smaller stocks than for larger stocks (Amihud and Mendelson, 1986; Amihud, 2002), we are able to examine the reliability of our illiquidity measure by examining average illiquidity according to size group.

In the table, consistent with our expectation, we see that illiquidity is higher for small stocks than for large stocks. Also, as expected, small stocks have higher returns and higher volatility than large stocks. Table 1 shows that our proxies for illiquidity are constructed in a way that is consistent with the previous literature.

To investigate whether each illiquidity proxy measures a common component of illiquidity, we compute the correlations between market illiquidity proxies. Table 2 shows the results. We see that the correlations are highly significant in Pearson correlation tests in most cases. The highest correlation of 0.874 is shown for *ZR* and *ET* and the lowest value among positive and significant correlations is 0.101. However, *CS* is negatively correlated with most of the other measures in the table. This implies that our illiquidity proxies measure the systematic common component of illiquidity, but only with non-negligible levels of measure-specific components. This motivates our empirical exercises based on the principal component analysis in later sections.

4.2. Innovations of illiquidity

Consistent with the previous literature (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006, Korajczyk and Sadka, 2008; Lee, 2011), we find that market aggregation of illiquidity, which is formed by taking an equally-weighted average of stock illiquidity, is highly persistent.[6] The first-order autocorrelations vary from 0.19 (*PS*) to 0.89 (*ET*) and are highly significant at 1% level. Given the persistence of market illiquidity, we build the innovations through AR(2) filtering of illiquidity over the entire sample period, similar to Pástor and Stambaugh (2003) and Acharya and Pedersen (2005).

$$C_{M,t} = \rho_0 + \rho_1 C_{M,t-1} + \rho_2 C_{M,t-2} + u_{M,t}, \tag{19}$$

where C_M is market aggregate illiquidity and the residual $u_{M,t}$ is innovation in illiquidity. Since time-series fitting is carried out ex-post, AR(2) fitting over the full sample period may have a look-ahead bias. Despite this issue, there are two reasons we employ

[6] In unreported tests, we use the value-weighted average as our market aggregate illiquidity. The results are similar.

Table 1
Average of illiquidity and other stock characteristics by size portfolios.
The table shows the average monthly percentage returns and illiquidity proxies for 25 equally-weighted size portfolios. Each size group is rebalanced annually based on the total market value of a stock at the end of the previous year. The illiquidity measures we use are Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure (*ZR*), Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond et al. (1999; *LOT*), Roll's measure (1984; *RO*), the spread estimates of Corwin and Schultz (2012; *CS*), and Goyenko et al.'s effective tick (2009; *ET*). Market cap is the market capitalization (in U$ 1000) at the end of previous year, B/M is the book-to-market ratio, and St. Dev. is the standard deviation of portfolio returns over the sample period. The last column reports the average of the number of stocks included in each portfolio over the years.

Portfolio	Return	*RV*	*PS*	*ZR*	*LM12*	*LOT*	*RO*	*CS*	*ET*	Market Cap	*B*/*M*	St. Dev.	Average N
Small	0.0179	2.8003	0.0351	0.2188	25.4455	0.0170	0.0240	0.0041	0.0191	21,856	1.020	0.067	36.29
2	0.0112	1.6058	0.0260	0.2026	14.0192	0.0151	0.0217	0.0024	0.0144	48,463	1.004	0.066	36.80
3	0.0103	1.2339	0.0197	0.1904	10.1264	0.0145	0.0215	0.0020	0.0131	76,418	0.975	0.065	36.83
4	0.0105	0.9185	0.0148	0.1809	7.6075	0.0141	0.0208	0.0015	0.0116	107,153	0.937	0.066	36.80
5	0.0107	0.6970	0.0134	0.1718	5.7526	0.0134	0.0201	0.0011	0.0105	139,919	0.903	0.063	36.72
6	0.0099	0.5610	0.0125	0.1653	4.5948	0.0129	0.0195	0.0009	0.0097	177,631	0.894	0.063	36.88
7	0.0089	0.4821	0.0071	0.1629	3.8364	0.0127	0.0193	0.0007	0.0096	216,556	0.835	0.062	36.82
8	0.0103	0.3836	0.0075	0.1563	3.0632	0.0121	0.0187	0.0004	0.0086	260,492	0.835	0.061	36.81
9	0.0094	0.3298	0.0061	0.1513	2.3225	0.0119	0.0185	0.0003	0.0083	310,509	0.827	0.061	36.78
10	0.0090	0.2668	0.0039	0.1456	2.1672	0.0114	0.0180	0.0001	0.0078	366,718	0.812	0.061	36.73
11	0.0096	0.2303	0.0037	0.1394	1.5555	0.0109	0.0175	0.0000	0.0073	429,674	0.781	0.060	36.89
12	0.0096	0.1999	0.0039	0.1355	1.5269	0.0107	0.0171	−0.0001	0.0070	505,968	0.789	0.060	36.80
13	0.0090	0.1592	0.0030	0.1336	1.3145	0.0104	0.0168	0.0000	0.0066	592,770	0.764	0.059	36.11
14	0.0093	0.1424	0.0020	0.1321	1.0491	0.0100	0.0163	0.0000	0.0064	695,329	0.767	0.055	36.80
15	0.0098	0.1075	0.0021	0.1267	0.6597	0.0097	0.0158	−0.0001	0.0060	822,009	0.745	0.053	36.73
16	0.0099	0.0886	0.0014	0.1219	0.5949	0.0093	0.0152	−0.0001	0.0055	965,536	0.748	0.054	36.89
17	0.0092	0.0776	0.0011	0.1208	0.5478	0.0093	0.0153	−0.0002	0.0056	1,148,042	0.720	0.053	36.78
18	0.0087	0.0621	0.0010	0.1157	0.4853	0.0090	0.0151	−0.0002	0.0052	1,380,448	0.679	0.053	36.81
19	0.0088	0.0499	0.0007	0.1100	0.3621	0.0087	0.0148	−0.0003	0.0048	1,702,496	0.700	0.053	36.82
20	0.0086	0.0348	0.0006	0.1071	0.1189	0.0084	0.0143	−0.0002	0.0045	2,159,283	0.686	0.051	36.72
21	0.0083	0.0250	0.0001	0.1043	0.0944	0.0082	0.0139	−0.0002	0.0043	2,834,792	0.689	0.050	36.88
22	0.0079	0.0203	0.0002	0.0996	0.0449	0.0078	0.0136	0.0000	0.0040	3,887,811	0.695	0.047	36.80
23	0.0081	0.0150	0.0002	0.0937	0.0662	0.0074	0.0131	−0.0001	0.0037	5,570,656	0.662	0.045	36.83
24	0.0071	0.0083	0.0000	0.0833	0.0103	0.0071	0.0129	−0.0001	0.0033	9,200,774	0.611	0.046	36.80
Large	0.0076	0.0030	−0.0001	0.0656	0.0041	0.0063	0.0120	−0.0001	0.0025	35,241,739	0.494	0.042	36.32

Table 2
Correlation of illiquidity measures.
This table shows the correlation between proxies for market aggregate illiquidity, formed by taking the equally-weighted average of stock illiquidity. The illiquidity measures we use are Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure (*ZR*), Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond et al. (1999; *LOT*), Roll's measure (1984; *RO*), the spread estimates of Corwin and Schultz (2012; *CS*), and Goyenko et al.'s effective tick (2009; *ET*). The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, from the Pearson correlation tests.

	RV	*ZR*	*RO*	*PS*	*LM12*	*LOT*	*CS*
ZR	0.471***						
RO	0.287***	−0.230***					
PS	0.496***	0.194***	0.210***				
LM12	0.718***	0.688***	−0.087**	0.314***			
LOT	0.654***	0.442***	0.565***	0.341***	0.586***		
CS	0.008	−0.034	−0.074*	−0.130***	−0.055	−0.193***	
ET	0.725***	0.874***	0.101**	0.292***	0.790***	0.687***	−0.066

the ex-post AR(2) fitting approach. First, a liquidity-related event is more explicitly shown by an ex-post AR(2) fitting. Second, since Acharya and Pedersen (2005) use the ex-post AR(2) fitting approach to obtain illiquidity innovation, we closely follow their method so that we have a better opportunity to examine whether their empirical results can be generalized across different illiquidity measures.

Following Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), we scale *PS* and *RV* by the ratio of the total market value at the end of month $t-1$ to that in August 1962, $MV_{M,t}/MV_{M,1}$. This is to adjust the time trend of the measures due to different values of currency over time. Hence, we use the following AR(2) fitting for *PS* and *RV*:

$$C_{M,t}\cdot\left(\frac{MV_{M,t-1}}{MV_{M,1}}\right)=\rho_0+\rho_{1,}C_{M,t-1}\cdot\left(\frac{MV_{M,t-1}}{MV_{M,1}}\right)+\rho_2 C_{M,t-2}\cdot\left(\frac{MV_{M,t-1}}{MV_{M,1}}\right)+u_{M,t}. \tag{20}$$

Note that the ratio of total market capitalization for month t are uniformly used for months t, $t-1$, and $t-2$ in the above regression, as in Acharya and Pedersen (2005), since we do not want the market capitalization ratio to unduly impact the construction of the innovations.[7] The coefficients ρ_1 and ρ_2 are all significant at the conventional 1% level, while the residuals from Eq. (20) are not significantly serially correlated, validating the use of $u_{M,t}$as the innovation in market illiquidity. We compute the innovations of stock-level illiquidity in a similar fashion.

Fig. 1 shows the time-series plot of innovations in market aggregate illiquidity. We see that the innovations in market aggregate illiquidity generally coincide with anecdotal liquidity-related events such as November 1973 (oil shock), October 1987 (stock market crash), September 1998 (Long-Term Capital Management), and September to October 2008 (Lehman Brothers). The fact that time-series plots of market illiquidity shocks by different measures jointly indicate the anecdotal events of dried-up liquidity implies the possibility that each measure proxies for the systematic and common component of liquidity.

4.3. Estimation of beta

Given the level of noises in estimated betas (i.e., errors-in-variable), we estimate liquidity risks at the portfolio level, while using individual stocks as test assets in the regression stage. Choosing individual stocks as test assets has both benefits and costs. First, we can minimize the potential loss of information contained in each stock which may be caused by portfolio formation. Second, more importantly, as Brennan et al. (1998) and Berk (2000) show, cross-sectional regression results can vary across portfolios that are formed based on firm characteristics. The use of individual stocks may prevent controversy when the test results vary according to the test assets used. Third, a stock-level analysis can help increase the power of the test by providing a large number of observations. On the cost side, however, the betas estimated at the level of individual stocks may be highly noisy. Considering these benefits and cost, as with Lee (2011) and similar to Fama and French (1992), we estimate market risk and liquidity risks at the portfolio level and subsequently assign these estimated loadings to individual stocks.

The detailed procedure is as follows. To estimate the post-ranking beta k ($k=1,\dots,4$), we first estimate for each stock i the beta k ($k=1,\dots,4$) of year t (pre-ranking beta) by Eq. (3) using the monthly returns and innovations of illiquidity over the years $t-5$ to $t-1$. To have a pre-ranking beta k of year t, stocks should have at least 36 monthly returns and innovations in illiquidity within the five-year estimation window. Based on the estimated pre-ranking beta k of stock i for year t, we sort stocks into ten equally weighted portfolios every year.[8] Subsequently, we estimate the beta k of portfolio p (post-ranking beta) for all ten portfolios by Eq. (3) over the sample period.

[7] Unlike Acharya and Pedersen (2005) and as in Lee (2011), we do not use innovations in *returns* in computing betas in the LCAPM. It is because return series is not persistent, while illiquidity is.

[8] While Fama and French (1992) formed portfolios in a two-dimensional sorting based on size and pre-ranking beta, we form portfolios on the basis of one-dimensional sorting based solely on pre-ranking beta (Lee, 2011), since one-dimensional sorting helps avoid potential bias due to the use of characteristic-based sorting.

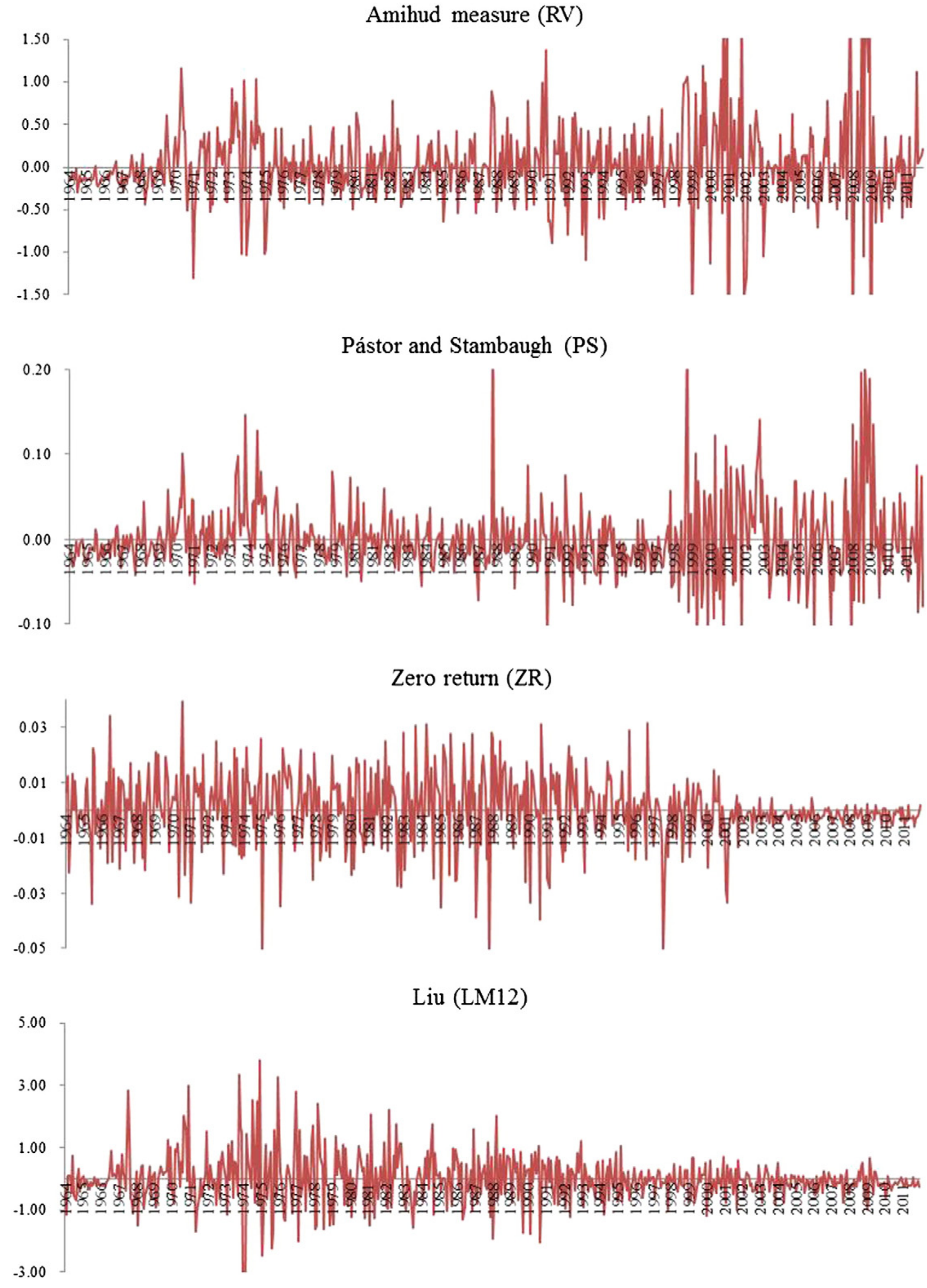

Fig. 1. Time-series plot of innovations in aggregate illiquidity.
The figure shows the time-series of innovations in market aggregate illiquidity that is formed by taking an equally weighted average of stock illiquidity. The illiquidity measures we use are Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure (*ZR*), Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond et al. (1999; *LOT*), Roll's measure (1984; *RO*), the spread estimates of Corwin and Schultz (2012; *CS*), and Goyenko et al.'s effective tick (2009; *ET*).

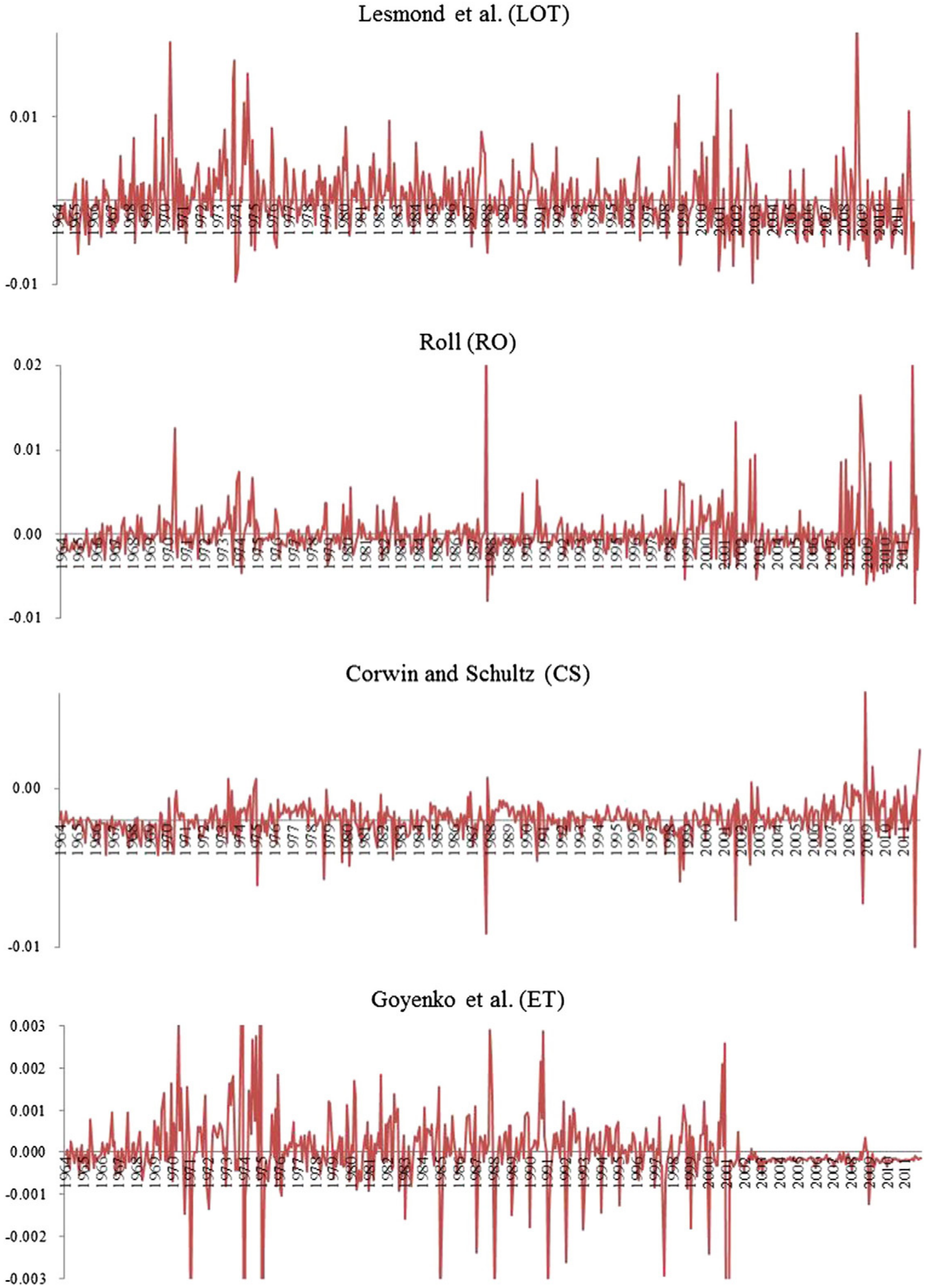

Fig. 1 (*continued*).

By this step, each of ten portfolios sorted on pre-ranking beta k has one post-ranking beta k. We assign this post-ranking beta k of portfolio p to all stocks that belong to portfolio p in that year. We obtain all four betas by repeating this procedure for all k's and compute the liquidity net beta by Eq. (4) for each stock. When this process is done, we have a total of 2762 stocks to be used for all analyses. We use stock returns and illiquidity as well as post-ranking betas obtained this way in our cross-sectional regressions below. The formation of

Table 3
Post-ranking betas.
For each stock i, we estimate the beta k ($k = 1,\ldots,4$) of year t (pre-ranking beta) by Eq. (3) using the monthly returns and innovations of illiquidity over the years $t-5$ to $t-1$. To have a pre-ranking beta k of year t, stocks should have at least 36 monthly returns and innovations in illiquidity within the five-year estimation window. Based on the pre-ranking beta k of year t, we sort 2762 stocks into ten equally weighted portfolios every year. Subsequently, we estimate the beta k of portfolio p (post-ranking beta) for all ten portfolios by Eq. (3) over the sample period. By this step, each of ten portfolios sorted on pre-ranking beta k has one post-ranking beta k. The table reports the post-ranking beta k (as shown at the top row) for the ten portfolios sorted on the corresponding pre-ranking beta, i.e., beta k. The illiquidity measures we use are Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure (*ZR*), Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond et al. (1999; *LOT*), Roll's measure (1984; *RO*), the spread estimates of Corwin and Schultz (2012; *CS*), and Goyenko et al.'s effective tick (2009; *ET*).

Portfolio	Beta 1	Beta 2	Beta 3	Beta 4	Beta 1	Beta 2	Beta 3	Beta 4	Beta 1	Beta 2	Beta 3	Beta 4	Beta 1	Beta 2	Beta 3	Beta 4
	Panel A. Amihud (*RV*)				Panel B. Pástor and Stambaugh (*PS*)				Panel C. Zero return (*ZR*)				Panel D. Liu (*LM12*)			
Low	0.0049	0.3571	−0.0556	−0.0807	0.2616	0.4346	−0.1546	−0.4076	0.6036	0.0671	−0.0370	−0.0176	0.0023	0.7926	0.0031	0.0120
2	0.0054	0.0170	−0.0449	−0.0262	0.2903	0.1086	−0.1428	−0.0667	0.6699	0.0627	−0.0253	−0.0008	0.0025	0.1059	0.0033	−0.0024
3	0.0063	0.0318	−0.0368	−0.0168	0.3366	0.0129	−0.1317	−0.0383	0.7766	0.0615	−0.0193	−0.0056	0.0029	0.0197	0.0037	−0.0020
4	0.0069	0.0220	−0.0341	−0.0102	0.3718	0.0073	−0.1234	−0.0096	0.8580	0.0661	−0.0111	0.0003	0.0032	0.0054	0.0027	0.0017
5	0.0075	0.0498	−0.0289	−0.0064	0.4017	0.0111	−0.1205	−0.0032	0.9269	0.0590	−0.0070	0.0050	0.0035	0.0066	0.0046	0.0000
6	0.0080	0.0645	−0.0249	−0.0036	0.4279	0.0322	−0.1120	−0.0101	0.9873	0.0595	−0.0118	0.0199	0.0037	0.0581	0.0041	−0.0002
7	0.0085	0.1027	−0.0215	−0.0026	0.4559	0.0733	−0.0972	−0.0075	1.0520	0.0655	−0.0076	0.0162	0.0039	0.0415	0.0052	−0.0001
8	0.0091	0.2900	−0.0203	−0.0011	0.4847	0.0670	−0.0938	−0.0422	1.1184	0.0729	−0.0058	0.0071	0.0042	0.1190	0.0056	−0.0021
9	0.0100	0.5076	−0.0150	−0.0012	0.5353	0.2081	−0.0973	−0.0621	1.2352	0.0697	−0.0069	0.0008	0.0046	0.5380	0.0059	−0.0019
High	0.0112	1.8760	−0.0154	−0.0199	0.6000	0.9975	−0.1028	−0.1658	1.3845	0.0592	−0.0116	0.0171	0.0052	1.9568	0.0082	0.0076
	Panel E. Lesmond et al. (*LOT*)				Panel F. Roll (*RO*)				Panel G. Corwin and Schultz (*CS*)				Panel H. Goyenko et al. (*ET*)			
Low	0.6275	0.0013	−0.0224	−0.0112	0.6174	0.0032	−0.0312	−0.0165	0.6485	0.0005	0.0053	0.0037	0.6341	0.0003	−0.0180	−0.0069
2	0.6963	0.0011	−0.0189	−0.0102	0.6851	0.0032	−0.0265	−0.0180	0.7196	0.0005	0.0052	0.0051	0.7037	0.0001	−0.0149	−0.0041
3	0.8073	0.0011	−0.0170	−0.0110	0.7943	0.0035	−0.0265	−0.0182	0.8343	0.0005	0.0052	0.0040	0.8158	0.0002	−0.0130	−0.0046
4	0.8919	0.0014	−0.0156	−0.0082	0.8776	0.0035	−0.0240	−0.0180	0.9218	0.0006	0.0053	0.0047	0.9014	0.0002	−0.0119	−0.0043
5	0.9635	0.0012	−0.0148	−0.0082	0.9480	0.0034	−0.0214	−0.0159	0.9958	0.0006	0.0057	0.0048	0.9737	0.0002	−0.0110	−0.0037
6	1.0263	0.0014	−0.0134	−0.0084	1.0098	0.0036	−0.0212	−0.0161	1.0607	0.0006	0.0052	0.0041	1.0372	0.0003	−0.0097	−0.0033
7	1.0935	0.0014	−0.0131	−0.0088	1.0760	0.0037	−0.0202	−0.0162	1.1302	0.0006	0.0057	0.0038	1.1052	0.0002	−0.0086	−0.0022
8	1.1626	0.0015	−0.0118	−0.0094	1.1439	0.0038	−0.0194	−0.0149	1.2015	0.0006	0.0058	0.0060	1.1749	0.0004	−0.0072	−0.0026
9	1.2839	0.0016	−0.0108	−0.0099	1.2633	0.0041	−0.0204	−0.0177	1.3270	0.0007	0.0063	0.0053	1.2976	0.0005	−0.0059	−0.0036
High	1.4392	0.0017	−0.0130	−0.0088	1.4161	0.0043	−0.0208	−0.0200	1.4874	0.0008	0.0071	0.0061	1.4545	0.0007	−0.0053	−0.0061

Table 4
Cross-sectional regressions using individual stocks as test assets.
For each stock *i*, we estimate the beta *k* (k = 1,…,4) of year *t* (pre-ranking beta) by Eq. (3) using the monthly returns and innovations of illiquidity over the years *t* - 5 to *t* - 1. To have a pre-ranking beta *k* of year t, stocks should have at least 36 monthly returns and innovations in illiquidity within the five-year estimation window. Based on the pre-ranking beta *k* of year *t*, we sort stocks into ten equally weighted portfolios every year. Subsequently, we estimate the beta *k* of portfolio *p* (post-ranking beta) for all ten portfolios by Eq. (3) over the sample period. By this step, each of ten portfolios sorted on pre-ranking beta *k* has one post-ranking beta *k*. We assign the post-ranking beta *k* of portfolio *p* to all stocks that belong to portfolio *p* in that year. We obtain all four betas by repeating this procedure for all *k*s and compute the liquidity net beta, Beta 5, by Eq. (4) for each stock. We perform the following cross-sectional regressions for each month using stock returns and post-ranking betas for 2762 stocks.

$$E\left(R_{i,t}-R_{f,t}\right)=a+bE\left(C_{i,t}\right)+\lambda_1\hat{\beta}^1_{i,t}+\lambda_2\hat{\beta}^2_{i,t}+\lambda_3\hat{\beta}^3_{i,t}+\lambda_4\hat{\beta}^4_{i,t} \tag{21}$$

The table shows the time-series averages of the estimated coefficients, together with the t-values in italics. The illiquidity measures we use are Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure (*ZR*), Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond et al. (1999; *LOT*), Roll's measure (1984; RO), the spread estimates of Corwin and Schultz (2012; *CS*), and Goyenko, Holden and Trzcinka's effective tick (2009; ET). *Illiq* is the previous 12 months' average of a given illiquidity measure. *lnMV* is the log of the market capitalization in US dollars, and *lnBM* is the log of the book-to-market ratio. The coefficient of *lnMV* is multiplied by 10^3, and *Illiq* is tested against the alternative hypothesis of positive coefficients, while the others are two-tailed tests. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Intercept	*Illiq*	Beta 1	Beta 2	Beta 3	Beta 4	Beta 5	*lnMV*	*lnBM*
Panel A. Amihud (RV)								
0.0197***	0.0013	0.2565				−0.0027***	−0.0011***	0.0018***
3.90	*0.77*	*0.69*				*−5.32*	*−3.11*	*2.94*
0.0159***	−0.0031	0.1661	0.0008				−0.0008**	0.0020***
3.14	*−1.80*	*0.44*	*1.17*				*−2.23*	*3.21*
0.0175***	−0.0027	0.1404		−0.0099			−0.0009***	0.0019***
3.48	*−1.66*	*0.42*		*−0.31*			*−2.60*	*3.04*
0.0160***	−0.0040	0.1639			−0.0282**		−0.0008**	0.0020***
3.14	*−2.27*	*0.44*			*−2.00*		*−2.25*	*3.23*
Panel B. Pástor and Stambaugh (PS)								
0.0170***	0.0199	0.0035				−0.0010**	−0.0009**	0.0019***
3.52	*0.94*	*0.50*				*−2.23*	*−2.54*	*3.05*
0.0128**	0.0096	0.0032	0.0009				−0.0006*	0.0019***
2.53	*0.48*	*0.45*	*0.85*				*−1.66*	*3.13*
0.0090*	0.0072	−0.0006		−0.0498***			−0.0006*	0.0021***
1.87	*0.34*	*−0.09*		*−2.79*			*−1.77*	*3.33*
0.0151***	0.0136	0.0035			0.0023		−0.0007**	0.0020***
3.05	*0.66*	*0.49*			*0.91*		*−2.15*	*3.17*
Panel C. Zero return (ZR)								
0.0147**	−0.0086	0.0014				0.0009	−0.0007*	0.0020***
2.58	*−0.71*	*0.48*				*0.54*	*−1.82*	*3.35*
0.0156**	−0.0102	0.0012	0.0018				−0.0007*	0.0020***
2.57	*−0.84*	*0.43*	*0.05*				*−1.96*	*3.37*
0.0154***	−0.0106	0.0019		0.0045			−0.0007**	0.0020***
2.71	*−0.88*	*0.63*		*0.18*			*−2.02*	*3.39*
0.0155***	−0.0095	0.0013			−0.0124		−0.0007*	0.0020***
2.71	*−0.78*	*0.45*			*−0.84*		*−1.92*	*3.42*
Panel D. Liu (LM12)								
0.0161***	−0.0001	0.3508				−0.0077***	−0.0008**	0.0019***
3.15	*−0.66*	*0.44*				*−3.30*	*−2.25*	*3.07*
0.0159***	−0.0001	0.3560	−0.0006				−0.0008**	0.0018***
3.04	*−1.00*	*0.44*	*−1.18*				*−2.14*	*3.01*
0.0148***	−0.0001	0.2707		0.1126			−0.0007**	0.0019***
2.91	*−1.43*	*0.33*		*0.54*			*−2.06*	*3.09*
0.0153***	−0.0001	0.3606			−0.0542		−0.0008**	0.0019***
2.96	*−1.33*	*0.45*			*−1.11*		*−2.08*	*3.04*
Panel E. Lesmond et al. (LOT)								
0.0137***	0.0879	0.0012				−0.0150	−0.0006**	0.0018***
3.10	*0.65*	*0.48*				*−0.82*	*−2.32*	*2.97*
0.0122**	0.0808	0.0008	0.2752				−0.0006**	0.0019***
2.55	*0.58*	*0.32*	*0.22*				*−2.02*	*3.16*
0.0126***	0.0656	0.0004		−0.0578			−0.0006**	0.0019***
2.71	*0.48*	*0.16*		*−0.54*			*−2.09*	*3.19*
0.0131***	0.0749	0.0011			0.0732		−0.0006**	0.0019***
2.80	*0.54*	*0.45*			*0.47*		*−2.03*	*3.17*
Panel F. Roll (RO)								
0.0170***	−0.0958	0.0020				−0.0079	−0.0008***	0.0017***
3.69	*−0.93*	*0.87*				*−0.69*	*−2.79*	*2.83*
0.0166***	−0.1185	0.0020	−0.0630				−0.0008***	0.0018***

(*continued on next page*)

Table 4 (*continued*)

Intercept	*Illiq*	Beta 1	Beta 2	Beta 3	Beta 4	Beta 5	*lnMV*	*lnBM*
Panel F. Roll (RO)								
3.40	*−1.12*	*0.85*	*−0.09*				*−2.65*	*3.01*
0.0123**	−0.1204	0.0006		−0.2047**			−0.0007**	0.0018***
2.48	*−1.15*	*0.25*		*−2.13*			*−2.44*	*2.94*
0.0206***	−0.1134	0.0022			0.2429**		−0.0008***	0.0018***
4.05	*−1.07*	*0.91*			*2.00*		*−2.72*	*2.98*
Panel G. Corwin and Schultz (CS)								
0.0153***	−0.2001	0.0013				0.0428	−0.0007**	0.0020***
3.44	*−1.27*	*0.51*				*1.31*	*−2.22*	*3.32*
0.0133***	−0.1923	0.0005	2.6156				−0.0007**	0.0021***
2.83	*−1.18*	*0.21*	*0.96*				*−2.00*	*3.46*
0.0132**	−0.1883	0.0012		0.1504			−0.0006**	0.0021***
2.49	*−1.18*	*0.45*		*0.29*			*−1.97*	*3.54*
0.0145***	−0.1994	0.0009			0.0459		−0.0007**	0.0021***
3.11	*−1.23*	*0.35*			*0.19*		*−2.03*	*3.42*
Panel H. Goyenko et al. (ET)								
0.0152***	−0.2562	0.0024				−0.0669**	−0.0008**	0.0020***
3.24	*−0.66*	*0.88*				*−2.24*	*−2.50*	*3.24*
0.0149***	−0.2381	0.0016	−0.0614				−0.0007**	0.0021***
3.12	*−0.60*	*0.57*	*−0.04*				*−2.28*	*3.52*
0.0145***	−0.3293	0.0003		−0.0995			−0.0007**	0.0022***
2.95	*−0.87*	*0.13*		*−0.97*			*−2.09*	*3.58*
0.0143***	−0.2826	0.0016			−0.0772		−0.0007**	0.0021***
3.01	*−0.71*	*0.57*			*−0.54*		*−2.19*	*3.47*

portfolios based on pre-ranking beta is widely used in the literature on empirical asset pricing, since the estimation of post-ranking beta for pre-ranking beta portfolios provides a wide dispersion of estimates across portfolios, while minimizing the loss of information that might be caused by portfolio formation (Fama and MacBeth, 1973).

Table 3 shows the post-ranking beta k (as shown at the top row) for the ten portfolios sorted on the corresponding pre-ranking beta, i.e., beta k, by different measures of illiquidity in separate panels. The commonality beta is positive for all the illiquidity measures and β^3 and β^4 have negative values for all measures but *ZR*, *LM12* and *CS*. As expected, we generally see monotonic patterns and a wide dispersion in the distribution of post-ranking betas according to pre-ranking beta portfolios.

5. Empirical results

We employ two different test methods in this paper: the traditional two-pass cross-sectional regression and the factor model regression. Using the two different methods also provides an opportunity to examine the robustness of the test results.

5.1. Cross-sectional regression

We run cross-sectional regressions every month using the individual stock returns and estimated post-ranking betas:

$$E\left(R_{i,t}-R_{f,t}\right) = a + bE\left(C_{i,t}\right) + \lambda_1\hat{\beta}^1_{i,t} + \lambda_2\hat{\beta}^2_{i,t} + \lambda_3\hat{\beta}^3_{i,t} + \lambda_4\hat{\beta}^4_{i,t}. \tag{21}$$

We use the average monthly illiquidity obtained from the previous 12 months (requiring at least nine months with valid data) as a proxy for expected illiquidity at time t, $E(C_{i,t})$. If the LCAPM holds, the intercept should not be, and the premiums for liquidity risks should be significantly different from zero. Since the frequency of data matters in testing the significance of the premium for the level of illiquidity, we test the null hypothesis of the zero illiquidity premium against the alternative hypothesis of the positive illiquidity premium (Lee, 2011). Eqs. (2) and (21) imply that $\lambda_1 = \lambda_2 = -\lambda_3 = -\lambda_4$ holds. To examine the specification of the model, we also test this hypothesis of the equality of risk premiums. The regressions include the log of market capitalization at the end of the previous year and the log of the book-to-market ratio. The book-to-market ratio at the end of year $t - 1$ is used for July of year t through June of year $t + 1$. Table 4 reports the empirical results of the cross-sectional regressions.

Consistent with Acharya and Pedersen (2005), Table 4 shows that the coefficient of β^4 is negative and significant at the 5% level for *RV*. The premiums are 0.028 with a t-value of 2.00. This is not just statistically significant but also economically significant. By multiplying the estimated coefficient to the difference in post-ranking β^4s between the highest and the lowest β^4-portfolios from Table 3, we obtain the annual premium of 2.06% for β^4 based on *RV*. That is,

$$\left(\beta^{4,\mathrm{P10}}-\beta^{4,\mathrm{P1}}\right) * 0.028 * 12 = 2.06\%, \tag{22}$$

Table 5
Cross-sectional regressions using 25 size-B/M portfolios as test assets.
We form 25 size-B/M portfolios every year based on market capitalization and book-to-market ratio using 2,762 stocks from the NYSE and the Amex. For each portfolio *i*, we estimate the beta *k* (*k*=1,…,4) using the monthly returns and innovations of illiquidity over the sample period. Market aggregate illiquidity and portfolio illiquidity are formed by taking an equally weighted average of stock illiquidity. With all four betas obtained by repeating this procedure for all k, we compute the liquidity net beta, Beta 5, as in Eq. (4). We perform the following cross-sectional regressions for each month, using portfolio returns and estimated betas.

$$E\left(R_{i,t}-R_{f,t}\right) = a + bE(C_{i,t}) + \lambda_1\hat{\beta}^1_{i,t} + \lambda_2\hat{\beta}^2_{i,t} + \lambda_3\hat{\beta}^3_{i,t} + \lambda_4\hat{\beta}^4_{i,t} \tag{21}$$

The table shows the time-series averages of the estimated coefficients, together with the *t*-values in italics. The illiquidity measures we use are Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure (*ZR*), Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond et al. (1999; *LOT*), Roll's measure (1984; *RO*), the spread estimates of Corwin and Schultz (2012; *CS*), and Goyenko, Holden and Trzcinka's effective tick (2009; *ET*). *Illiq* is the previous 12 months' average of a given illiquidity measure. *Illiq* is tested against the alternative hypothesis of positive coefficients, while the others are two-tailed tests. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Intercept	*Illiq*	Beta 1	Beta 2	Beta 3	Beta 4	Beta 5
Panel A. Amihud measure (RV)						
0.0199***	0.0071*	−2.0092***				−0.0007
6.11	*1.65*	*−4.02*				*−1.46*
0.0199***	0.0072 **	−2.0144***	−0.0007			
6.11	*1.66*	*−4.03*	*−1.46*			
0.0287***	−0.0054	−4.4188***		−0.4115***		
7.27	*−1.92*	*−5.77*		*−3.94*		
0.0191***	0.0038	−1.8996***			0.0303	
5.94	*0.99*	*−3.83*			*1.29*	
Panel B. Pástor and Stambaugh (PS)						
0.0191***	0.0586	−0.0341***				0.0005
5.87	*0.52*	*−3.70*				*0.91*
0.0191***	0.0523	−0.0340***	0.0007			
5.84	*0.45*	*−3.67*	*1.08*			
0.0191***	−0.0088	−0.0572***		−0.0834***		
5.60	*−0.08*	*−5.39*		*−3.82*		
0.0189***	0.0181	−0.0334***			−0.0012	
5.86	*0.16*	*−3.64*			*−0.51*	
Panel C. Zero return (ZR)						
0.0123***	0.0330*	−0.0138***				0.0056
3.17	*1.34*	*−3.47*				*0.56*
0.0115***	0.0323*	−0.0135***	0.0065			
2.84	*1.33*	*−3.28*	*0.38*			
0.0119***	0.0513**	−0.0134***		0.0187		
3.40	*2.15*	*−3.51*		*0.51*		
0.0126***	0.0326	−0.0138***			−0.0092	
2.95	*1.23*	*−3.23*			*−0.56*	
Panel D. Liu (LM12)						
0.0193***	0.0001	−4.4232***				0.0014**
5.69	*0.37*	*−3.78*				*2.48*
0.0193***	0.0001	−4.4259***	0.0013**			
5.69	*0.37*	*−3.78*	*2.48*			
0.0188***	0.0004***	−5.1831***		0.4830**		
5.84	*2.39*	*−3.98*		*2.02*		
0.0198***	0.0003	−4.5333***			0.0829	
5.89	*0.98*	*−3.90*			*1.23*	
Panel E. Lesmond et al. (LOT)						
0.0212***	0.2982	−0.0286***				0.3759***
5.94	*1.17*	*−5.70*				*3.56*
0.0183***	0.7248***	−0.0217***	1.0129			
5.41	*2.90*	*−5.41*	*1.54*			
0.0215***	0.2304	−0.0298***		−0.7852***		
5.96	*0.87*	*−6.12*		*−4.30*		
0.0181***	0.6939***	−0.0218***			−0.1884	
5.45	*2.80*	*−5.23*			*−1.36*	
Panel F. Roll (RO)						
0.0114***	0.2095	−0.0279***				0.4157***
3.43	*1.18*	*−5.86*				*4.78*
0.0239***	0.4546***	−0.0169***	−2.2621**			
6.51	*2.44*	*−3.80*	*−2.54*			

(continued on next page)

Table 5 (*continued*)

Intercept	*Illiq*	Beta 1	Beta 2	Beta 3	Beta 4	Beta 5
0.0197***	0.0807	−0.0311***		−0.6721***		
6.04	*0.45*	*−6.45*		*−5.50*		
0.0160 ***	0.4696***	−0.0207***			−0.1520	
4.88	*2.52*	*−4.96*			*−1.43*	
Panel G. Corwin and Schultz (CS)						
0.0153***	1.2416***	−0.0124**				−0.2223
4.12	*3.21*	*−2.41*				*−1.28*
0.0165***	0.5926*	−0.0200***	15.1438***			
4.30	*1.61*	*−4.05*	*3.19*			
0.0162***	0.8835**	−0.0147***		0.6547*		
4.20	*2.33*	*−2.66*		*1.66*		
0.0152***	1.2175***	−0.0109**			0.2033	
4.13	*3.22*	*−2.35*			*0.94*	
Panel H. Goyenko et al. (ET)						
0.0192***	−0.2949	−0.0158***				0.2768***
5.41	*−1.70*	*−3.91*				*3.33*
0.0191***	−0.2038	−0.0127***	3.2371**			
5.36	*−1.18*	*−3.31*	*2.12*			
0.0200***	−0.3337	−0.0227***		−0.8256***		
5.44	*−2.17*	*−4.76*		*−4.36*		
0.0173***	−0.0380	−0.0108***			−0.2098*	
4.99	*−0.22*	*−2.90*			*−1.68*	

where $\beta^{4,P10}$ and $\beta^{4,P1}$ are values in Table 3 of post-ranking β^4s of the highest pre-ranking β^4-portfolio and the lowest pre-ranking β^4-portfolio, respectively. Similarly, the significant coefficient of β^4 based on *RO* amounts to the annual premium of 1.02%. Also, consistent with Pástor and Stambaugh (2003), *PS* and *RO* show that β^3 is significant and negative with premiums of 0.050 and 0.205, respectively. Combined with the highest and the lowest values of post-ranking β^3, shown in Table 3, these premiums produce annual returns of 3.10% and 2.57%, respectively. Contrary to our expectation, however, the liquidity net beta, β^5, is mostly insignificant or significant with a wrong sign. The model specification tests of $\lambda_1 = \lambda_2 = -\lambda_3 = -\lambda_4$ show that we could not reject the null hypothesis of the equality in risk premiums in all measures but *PS*, supporting the LCAPM.

5.2. Cross-sectional regressions at the portfolio level

In this section, we provide cross-sectional regression results using characteristic-based portfolios as test assets. For each portfolio, we estimate the beta k ($k = 1,\ldots,4$) using the monthly returns and innovations of illiquidity over the sample period. We perform the following cross-sectional regressions of Eq. (21) for each month using portfolio returns and estimated betas.

Table 5 shows the results for the case of 25 portfolios formed annually based on market capitalization and book-to-market ratio using the same 2762 stocks that are also used in the previous section. On average, we have 37.59 stocks in each of the 25 portfolios. Liquidity net beta, β^5, is significant and positive for *LM12*, *LOT*, *RO*, and *ET*. β^2 is priced for *LM12*, *CS*, and *ET*. Consistent with Pástor and Stambaugh (2003), β^3 is significant and negative for *RV*, *PS*, *LOT*, *RO*, and *ET*. However, β^4 is not significant only for *ET*. The pattern of pricing of each liquidity risk in this table contrasts with that in Table 4. To examine whether the characteristic of size-B/M portfolios contributes to the difference in results, we run cross-sectional regressions with 25 size portfolios and illiquidity portfolios. In Appendix A, Tables A1 and A2 report the empirical results based on size portfolios and illiquidity portfolios, respectively. We see that the pricing of liquidity risks varies across measures and test assets in most cases. Except for the cases of *PS* and *RO*, the results based on illiquidity portfolios show no evidence of significant pricing of liquidity risks. β^3 and β^4 are significantly priced for *CS* when the test asset is size portfolios, but the significance in results disappears when the test asset is illiquidity portfolios. Given this sensitivity in results based on test portfolios (Berk, 2000; Brennan et al., 1998), we mainly focus on the test based on individual stock as test assets.

5.3. Cross-sectional regressions based on the principal component analysis

In this section, we extract common components from eight different illiquidity measures for a given stock by principal component analysis and repeat the cross-sectional regression tests based on these common and systematic components.

Fig. 2 shows the plot of the average eigenvalue proportions of eight principal components in a bar graph together with the plot of cumulative proportions in a line graph. Consistent with Korajczyk and Sadka (2008), we find that the first principal component explains approximately 33% of the whole variation of eight illiquidity proxies, providing evidence of the existence of the systematic and common component of illiquidity across different measures of illiquidity.

Table 6 shows post-ranking betas based on the first principal component across eight measures of illiquidity. The estimation of post-ranking beta in this section follows the same procedure as specified in Section 4.3, except that we use the PCA-based

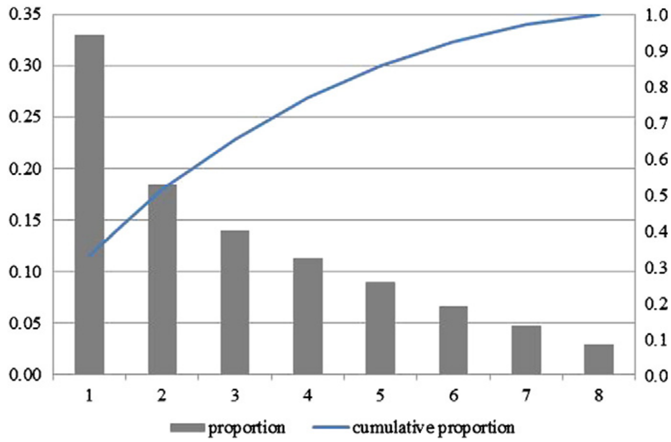

Fig. 2. Eigenvalue proportion of principal components.
The figure shows the plots of the proportion and the cumulative proportion of eight eigenvalues. Bar graphs correspond to the proportion of each principal component and are matched to the number of the left axis. The line graph is the cumulative proportion and is matched to the number of right axis.

measure of illiquidity in this section. In the table, we see wide and monotonic dispersion of post-ranking beta based on PCA, as we intended in the estimation procedure.

Table 7 shows the cross-sectional regression results when the stock illiquidity, market illiquidity, innovations in illiquidity, pre-ranking betas and post-ranking betas are all constructed based on the first principal component.

Consistent with the LCAPM, Table 7 provides evidence that liquidity risks based on the common and systematic component of liquidity are significantly priced beyond the level of illiquidity and the traditional market risk. Specifically, we see that the commonality beta is significantly priced at the 1% level with the coefficients of 0.004 and *t*-value of 2.61. Also consistent with the LCAPM, β^4 is significantly priced with a coefficient of −0.027 at a 5% significance level. By Eq. (22) combined with the values of post-ranking β^4s for the highest- and the lowest-decile portfolios in Table 6, we obtain the annual premiums of 2.28% for commonality beta and 2.42% for β^4, which are also economically significant.[9] In the test of the model specification, we could not reject the null hypothesis of the equality in liquidity risk premiums, supporting the LCAPM. By comparing the magnitude and significance of intercepts of Table 7 with those in Table 4, we see that the intercepts in Table 7 are smaller in magnitude and less significant than those from the corresponding specifications in Table 4. We interpret this as a slight improvement in performance of the model when we run the tests based on the principal component, compared to the cases of a single measure.

5.5. Factor model regressions

Another popular method to demonstrate the importance of liquidity risks in asset pricing is a factor model regression used in the previous studies (Pástor and Stambaugh, 2003; Korajczyk and Sadka, 2004; Lee, 2011). Factor model regressions may reduce the possibility of false inferences that may arise from errors-in-variable problems in two-stage cross-sectional regressions because it is the *rank*, not the estimated value, of pre-ranking betas that matters in the factor model regression. Moreover, the following factor model regressions directly show the returns from a "long-short" trading strategy, which is frequently employed by hedge funds, based on a specific source of risk. In doing so, the test also provides a convenient way to interpret the economic magnitude of pricing of liquidity risks since the intercept in the factor model regression indicates the abnormal returns that can be obtained after controlling for risks that are specified as factors in the regressions.

For each beta, we form ten portfolios sorted on the pre-ranking beta in the same way as in Section 4.3, but by using the illiquidity measure which is obtained based on the first principal component. We perform the following factor model regressions for each portfolio p ($p = 1,\dots,10$):

$$R_{k,p,t} - R_{f,t} = \alpha_{k,p} + \delta_{k,p}\left(R_{m,t} - R_{f,t}\right) + \xi_{k,p,t}, \tag{23}$$

$$R_{k,p,t} - R_{f,t} = \alpha^{FF}_{k,p} + \delta^{M}_{k,p}\left(R_{m,t} - R_{f,t}\right) + \delta^{S}_{k,p} SMB_t + \delta^{H}_{k,p} HML_t + \xi^{FF}_{k,p,t}, \tag{24}$$

$$R_{k,p,t} - R_{f,t} = \alpha^{FOUR}_{k,p} + \delta^{FOUR,M}_{k,p}\left(R_{m,t} - R_{f,t}\right) + \delta^{FOUR,S}_{k,p} SMB_t + \delta^{FOUR,H}_{k,p} HML_t + \delta^{FOUR,W}_{k,p} WML_t + \xi^{FOUR}_{k,p,t}. \tag{25}$$

[9] Acharya and Pedersen (2005) show the annualized premiums for β^2 and β^4 are 0.08% and 0.82%, respectively.

Table 6
Post-ranking betas based on the first principal component.
For each stock i, we estimate the beta k ($k = 1,\ldots,4$) of year t (pre-ranking beta) by Eq. (3) using the monthly returns and innovations of illiquidity over the years $t - 5$ to $t - 1$. To have a pre-ranking beta k of year t, stocks should have at least 36 monthly returns and innovations in illiquidity within the five-year estimation window. Based on the pre-ranking beta k of year t, we sort 2,762 stocks into ten equally weighted portfolios every year. Subsequently, we estimate the beta k of portfolio p (post-ranking beta) for all ten portfolios by Eq. (3) over the sample period. By this step, each of ten portfolios sorted on pre-ranking beta k has one post-ranking beta k. The table reports the post-ranking beta k (as shown at the top row) for the ten portfolios sorted on the corresponding pre-ranking beta, i.e., beta k. The illiquidity measure we use in this table is based on the first principal component (PCA) across Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure (*ZR*), Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond et al. (1999; *LOT*), Roll's measure (1984; *RO*), the spread estimates of Corwin and Schultz (2012; *CS*), and Goyenko et al.'s effective tick (2009; *ET*).

Portfolio	Beta 1	Beta 2	Beta 3	Beta 4
Low	0.0313	0.3722	−0.1807	−0.1118
2	0.0347	0.5844	−0.1540	−0.0836
3	0.0403	0.5904	−0.1365	−0.0801
4	0.0445	0.5706	−0.1271	−0.0780
5	0.0481	0.5914	−0.1136	−0.0797
6	0.0512	0.6779	−0.1076	−0.0680
7	0.0546	0.6869	−0.0955	−0.0658
8	0.0580	0.7547	−0.0871	−0.0602
9	0.0641	0.7660	−0.0724	−0.0655
High	0.0718	0.8140	−0.0649	−0.0359

Table 7
Cross-sectional regression of principal components.
For each stock i, we estimate the beta k ($k = 1,\ldots,4$) of year t (pre-ranking beta) using the monthly returns and innovations of the first principal component over the years $t - 5$ to $t - 1$. The market aggregate of illiquidity is formed by taking an equally-weighted average of the stocks' first principal component. To have a pre-ranking beta k of year t, stocks should have at least 36 monthly returns and innovations in the first principal component within the given five-year estimation window. Based on the pre-ranking beta k of year t, we sort stocks into ten equally weighted portfolios every year. Subsequently, we estimate the beta k of portfolio p (post-ranking beta) for all ten portfolios by Eq. (3) over the sample period. By this step, each of ten portfolios sorted on pre-ranking beta k has one post-ranking beta k. We assign the post-ranking beta k of portfolio p to all stocks that belong to portfolio p in that year. We obtain all four betas by repeating this procedure for all ks and compute the liquidity net beta, Beta 5, by Eq. (4) for each stock. We perform the following cross-sectional regressions for each month using stock returns and post-ranking betas for 2762 stocks.

$$E\left(R_{i,t}-R_{f,t}\right) = a + bE\left(C_{i,t}\right) + \lambda_1\hat{\beta}^1_{i,t} + \lambda_2\hat{\beta}^2_{i,t} + \lambda_3\hat{\beta}^3_{i,t} + \lambda_4\hat{\beta}^4_{i,t}$$

The table shows the time-series averages of the estimated coefficients, together with the t-values in italics. *Illiq* is the previous 12 months' average of the first principal component, *lnMV* is the log of the market capitalization in US dollars, and *lnBM* is the log of the book-to-market ratio. The coefficient of *lnMV* is multiplied by 10^3 and *Illiq* is tested against the alternative hypothesis of positive coefficients, while the others are two-tailed tests. The superscripts*,**, and*** denote significance at the 10%, 5%, and 1% levels, respectively.

Intercept	*Illiq*	Beta 1	Beta 2	Beta 3	Beta 4	Beta 5	*lnMV*	*lnBM*
0.0125^{***}	0.0022^{***}	0.0481				−0.0009	-0.0006^{*}	0.0017^{***}
2.73	*6.63*	*0.85*				*−1.59*	*−1.84*	*2.84*
0.0088^{*}	0.0019^{***}	0.0286	0.0043^{***}				−0.0005	0.0018^{***}
1.85	*5.18*	*0.49*	*2.61*				*−1.59*	*2.92*
0.0114^{**}	0.0019^{***}	0.0000		−0.0167			-0.0005^{*}	0.0017^{***}
2.52	*5.77*	*0.00*		*−1.15*			*−1.72*	*2.86*
0.0100^{**}	0.0019^{***}	0.0333			-0.0266^{**}		-0.0006^{*}	0.0018^{***}
2.13	*5.34*	*0.57*			*−2.39*		*−1.73*	*2.92*

$R_{k,p,t}$is an equally weighted return of portfolio p, which is formed based on pre-ranking beta k of year t, $R_{f,t}$ is a one-month US Treasury bill rate, and $R_{m,t}$ is a market index return. *SMB* and *HML*, which denote size and book-to-market factors, respectively, are obtained from Ken French's website.[10] *WML* is a momentum factor computed as return differences between winner and loser portfolios, as in Carhart (1997), downloaded from Wharton Research Data Services. The intercept, alpha, from each regression is the abnormal return in excess of compensation for factor risks. The abnormal returns from the zero-cost investment portfolio can be earned by going long on the highest decile portfolio and shorting the lowest decile portfolio based on liquidity risk k (henceforth 10–1 spread). Hence, significant 10–1 spread from long-short trading strategy based on beta k implies that beta k is a systematic source of risk beyond the factors specified in the factor model. That is, beta k is priced.

Table 8 shows the estimated intercepts (alphas) from the factor model regressions in Eqs. (23)–(25) for the betas in the LCAPM. Consistent with the results of cross-sectional regressions in the previous tables, we see evidence of pricing of liquidity

[10] We thank K. French for making the factor data available on the web.

Table 8
Factor model regressions with betas estimated based on the first principal component.
For each stock i, we estimate the beta k ($k = 1,\ldots,4$) of year t (pre-ranking beta) using the monthly returns and innovations of the first principal component over the years $t - 5$ to $t - 1$. The market aggregate of illiquidity is formed by taking an equally-weighted average of the stocks' first principal component. To have a pre-ranking beta k of year t, stocks should have at least 36 monthly returns and innovations in the first principal component within the given five-year estimation window. Liquidity net beta of stock i of year t, Beta 5, is computed from four pre-ranking betas of stock i of year t by Eq. (4). Based on the pre-ranking beta k of year t, we sort 2762 stocks into ten equally weighted portfolios every year. Each portfolio return in excess of the risk-free rate is regressed in a single-factor model (panel A), in a Fama and French (1993)'s three-factor model (panel B), and in a four-factor model (panel C), as shown in Eqs. (23)–(25), respectively.

$$R_{k,p,t} - R_{f,t} = \alpha_{k,p} + \delta_{k,p}\left(R_{m,t} - R_{f,t}\right) + \xi_{k,p,t}, \tag{23}$$

$$R_{k,p,t} - R_{f,t} = \alpha^{FF}_{k,p} + \delta^{M}_{k,p}\left(R_{m,t} - R_{f,t}\right) + \delta^{S}_{k,p} SMB_t + \delta^{H}_{k,p} HML_t + \xi^{FF}_{k,p,t}, \tag{24}$$

$$R_{k,p,t} - R_{f,t} = \alpha^{FOUR}_{k,p} + \delta^{FOUR,M}_{k,p}\left(R_{m,t} - R_{f,t}\right) + \delta^{FOUR,S}_{k,p} SMB_t + \delta^{FOUR,H}_{k,p} HML_t + \delta^{FOUR,W}_{k,p} WML_t + \xi^{FOUR}_{k,p,t} \tag{25}$$

$R_{k,p,t}$ is an equally weighted return of portfolio p, which is formed based on beta k at month t, $R_{f,t}$ is a one-month US Treasury bill rate, and $R_{m,t}$ is a market index return. *HML*, *SML*, and *WML* denote size factor, book-to-market factor, and momentum factor, respectively. The table shows the estimated alphas with the t-values in italics from the regression of each of the ten portfolios that are formed based on the liquidity risk specified in the column heading of the table. The last column labeled '10–1' shows the difference in the estimated intercepts from the regressions of the portfolios with the highest beta ($p = 10$) and of those with the lowest beta ($p = 1$). The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6	7	8	9	10	10–1
Panel A. CAPM alpha											
Beta 1	0.0038***	0.0036***	0.0045***	0.0040***	0.0037***	0.0031***	0.0040***	0.0034**	0.0026*	0.0012	−0.0026
	3.26	*3.58*	*5.05*	*3.93*	*3.49*	*2.60*	*3.06*	*2.44*	*1.68*	*0.57*	*−1.11*
Beta 2	0.0016	0.0024**	0.0026**	0.0027**	0.0035***	0.0033***	0.0037***	0.0043***	0.0050***	0.0055***	0.0039***
	1.53	*2.33*	*2.45*	*2.44*	*3.30*	*3.01*	*3.27*	*3.65*	*4.28*	*3.77*	*3.43*
Beta 3	0.0033	0.0035**	0.0027*	0.0045***	0.0028**	0.0036***	0.0036***	0.0030***	0.0030***	0.0040***	0.0007
	1.53	*2.10*	*1.88*	*3.50*	*2.54*	*3.62*	*3.71*	*3.32*	*3.37*	*3.65*	*0.30*
Beta 4	0.0064***	0.0048***	0.0039***	0.0031***	0.0027**	0.0027**	0.0037***	0.0021*	0.0026**	0.0027**	−0.0037***
	4.73	*4.13*	*3.38*	*2.93*	*2.46*	*2.54*	*3.55*	*1.81*	*2.33*	*2.46*	*−3.58*
Beta 5	0.0017*	0.0025**	0.0026**	0.0025**	0.0038***	0.0029**	0.0039***	0.0041***	0.0048***	0.0059***	0.0042***
	1.65	*2.51*	*2.42*	*2.35*	*3.47*	*2.57*	*3.53*	*3.36*	*3.83*	*3.93*	*3.50*
Panel B. Fama–French three factor model alpha											
Beta 1	0.0014	0.0013	0.0025***	0.0013*	0.0011	0.0001	0.0007	0.0000	−0.0009	−0.0022	−0.0036*
	1.35	*1.50*	*3.33*	*1.77*	*1.34*	*0.10*	*0.72*	*−0.05*	*−0.78*	*−1.34*	*−1.69*
Beta 2	−0.0013*	−0.0003	−0.0001	−0.0003	0.0006	0.0005	0.0007	0.0012	0.0022***	0.0024**	0.0037***
	−1.66	*−0.42*	*−0.17*	*−0.40*	*0.83*	*0.68*	*0.85*	*1.47*	*2.70*	*2.14*	*3.47*
Beta 3	−0.0010	−0.0005	−0.0010	0.0013	0.0001	0.0010	0.0011	0.0011	0.0011	0.0020**	0.0031
	−0.65	*−0.45*	*−1.01*	*1.43*	*0.06*	*1.39*	*1.47*	*1.40*	*1.43*	*2.06*	*1.57*
Beta 4	0.0034***	0.0018**	0.0008	0.0004	−0.0002	−0.0001	0.0010	−0.0011	−0.0003	−0.0001	−0.0035***
	3.21	*2.11*	*0.98*	*0.54*	*−0.20*	*−0.12*	*1.27*	*−1.35*	*−0.35*	*−0.11*	*−3.32*
Beta 5	−0.0010	−0.0002	−0.0003	−0.0003	0.0009	−0.0001	0.0009	0.0010	0.0017*	0.0028**	0.0038***
	−1.35	*−0.25*	*−0.38*	*−0.33*	*1.16*	*−0.07*	*1.19*	*1.15*	*1.93*	*2.41*	*3.41*
Panel C. Four factor model alpha											
Beta 1	0.0011	0.0013	0.0025***	0.0015**	0.0018**	0.0010	0.0023**	0.0016*	0.0015	0.0020	0.0009
	1.03	*1.51*	*3.17*	*2.02*	*2.18*	*1.14*	*2.49*	*1.65*	*1.47*	*1.44*	*0.50*
Beta 2	−0.0002	0.0008	0.0012	0.0005	0.0016**	0.0017**	0.0013	0.0026***	0.0032***	0.0049***	0.0051***
	−0.27	*0.99*	*1.54*	*0.66*	*2.14*	*2.27*	*1.62*	*3.16*	*4.05*	*4.71*	*4.77*
Beta 3	0.0027*	0.0019*	0.0008	0.0025***	0.0011	0.0019**	0.0016**	0.0012	0.0012	0.0019*	−0.0008
	1.93	*1.86*	*0.82*	*2.94*	*1.38*	*2.50*	*2.03*	*1.51*	*1.58*	*1.85*	*−0.45*
Beta 4	0.0055***	0.0032***	0.0021**	0.0015*	0.0010	0.0010	0.0021***	0.0000	0.0008	0.0007	−0.0047***
	5.62	*3.88*	*2.56*	*1.87*	*1.26*	*1.31*	*2.73*	*−0.03*	*0.97*	*0.94*	*−4.62*
Beta 5	0.0000	0.0004	0.0006	0.0008	0.0023***	0.0011	0.0018**	0.0020**	0.0032***	0.0053***	0.0053***
	−0.01	*0.47*	*0.83*	*1.04*	*2.96*	*1.33*	*2.34*	*2.32*	*3.86*	*5.13*	*4.86*

risks. The commonality beta is significant in all factor models at the conventional 1% level. In the Fama–French three factor model, the 10–1 spread based on the commonality beta is 0.37% (4.44% annually), which is also economically significant. Turning to β^4, the 1–10 spread,[11] which is formed by going long on the lowest-decile portfolio and shorting the highest-decile portfolio based on β^4, is also both statistically and economically significant in all factor models. The 1–10 spread in the Fama–French three factor model shows that monthly return of 0.35% (4.20% annually) can be obtained in excess of the return provided by bearing risks

[11] The LCAPM shows that β^3 and β^4 are negatively related to stock return. That is, returns of stocks with high β^3 or β^4 will be smaller than the returns of stocks with low β^3 or β^4. Hence, in order to materialize the positive abnormal returns from the negative 10–1 spread, investors should perform a corresponding 1–10 strategy for these liquidity risks.

specified in the Fama–French three factor model. The significant pricing of β^2 and β^4 drives the significant pricing of the liquidity net beta in all panels. Overall, the results in this section provide evidence supporting our previous findings of pricing of liquidity risks.

6. Conclusion

Each single measure of liquidity proposed in the previous literature is a proxy, with a potentially non-negligible amount of noise, for systematic liquidity that is common across different proxies or that is specific to a given proxy. Consistent with Korajczyk and Sadka (2008), we find that there exists a systematic and common component across different proxies of liquidity by showing that the first principal component explains about 33% of the whole variation of eight liquidity proxies. In subsequent analyses, we apply this systematic and common component of liquidity in testing the pricing implication of liquidity risks based on the LCAPM. While the empirical results based on a single measure are weak and vary according to the measure used in the test, the tests based on the first principal component show strong evidence of the pricing of liquidity risk, implying that it is the common underlying factor in measured liquidity that carries a significant premium.

Our tests of the LCAPM show that multiple sources of liquidity risks are jointly priced. Specifically, we find that investors are willing to accept a lower return for stocks whose liquidity increases in a down market or when the market liquidity dries up. Challenging the traditional inter-temporal capital asset pricing framework of Merton (1973), who argues that it is a covariance of stock return with market-level variable that is incorporated into the priced state variable, our findings imply that investors need to consider the easiness of liquidation of shares in a down market as well as in a market with dried-up liquidity. Overall, our findings provide supporting evidence of the LCAPM in that liquidity is a source of systematic risk that is independent from the traditional market risk.

It is worth noting that we do not consider the impact of different holding periods on liquidity in the empirical tests (Amihud and Mendelson (1986), Constantinides (1986), Atkins and Dyl (1997)). By using monthly return and liquidity, we implicitly assume that the investors' holding period is one month, which may be a strong assumption. Investigating the relation between holding periods and the multiple channel of the pricing of liquidity may be worthwhile for future studies.

Appendix A

Table A1

Cross-sectional regressions using 25 size portfolios as test assets.

We form 25 portfolios every year, based on the previous-year-end market capitalization using 2,762 stocks. For each portfolio i, we estimate the beta k (k=1,...,4) using the monthly returns and innovations of illiquidity over the sample period. Market aggregate illiquidity and portfolio illiquidity are formed by taking an equally weighted average of stock illiquidity. With all four betas obtained by repeating this procedure for all k, we compute the liquidity net beta, Beta 5, as in Eq. (4). We perform the following cross-sectional regressions for each month using portfolio returns and estimated betas.

$$E\left(R_{i,t}-R_{f,t}\right)=a+bE(C_{i,t})+\lambda_1\hat{\beta}^1_{i,t}+\lambda_2\hat{\beta}^2_{i,t}+\lambda_3\hat{\beta}^3_{i,t}+\lambda_4\hat{\beta}^4_{i,t} \tag{21}$$

The table shows the time-series averages of the estimated coefficients, together with the t-values in italics. The illiquidity measures we use are Amihudâs measure (2002; *RV*), Pástor and Stambaughâs measure (2003; *PS*), the zero-return measure *(ZR)*, Liuâs measure (2006; *LM12*), the illiquidity measure of Lesmond, Ogden, and Trzcinka (1999; *LOT*), Rollâs measure (1984; RO), the spread estimates of Corwin and Schultz (2012; CS), and Goyenko, Holden and Trzcinka's effective tick (2009; ET). *Illiq* is the previous 12 monthsâ average of a given illiquidity measure. *Illiq* is tested against the alternative hypothesis of positive coefficients, while the others are two-tailed tests. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Intercept	Illiq	Beta1	Beta2	Beta3	Beta4	Beta5
Panel A. Amihud measure (RV)						
-0.0012	-0.0031	0.6728				0.0010 *
-0.25	-0.47	0.95				1.82
-0.0012	-0.0038	0.6823	0.0010 *			
-0.26	-0.55	0.96	1.91			
-0.0004	0.0041 **	0.6773		0.0404		
-0.09	2.11	0.90		0.41		
-0.0006	0.0045 *	0.6074			0.0064	
-0.13	1.36	0.88			0.16	
Panel B. Pástor and Stambaugh (PS)						
-0.0031	-0.0604	0.0171				0.0015 ***
-0.60	-0.40	1.21				2.91
-0.0034	-0.0629	0.0182	0.0019 ***			
-0.66	-0.42	1.28	2.97			
-0.0007	-0.0690	-0.0186		-0.1114 ***		

Table A1 (*continued*)

Intercept	Illiq	Beta1	Beta2	Beta3	Beta4	Beta5
-0.13	-0.88	-1.29		-4.18		
-0.0018	-0.0137	0.0141			-0.0087 ***	
-0.35	-0.11	1.02			-3.11	
Panel C. Zero return (ZR)						
0.0015	0.0389 **	-0.0042				-0.0134 *
0.36	2.04	-0.87				-1.65
0.0024	0.0396 **	-0.0038	-0.0306 *			
0.56	2.04	-0.78	-1.85			
0.0065 *	0.0152	-0.0060		-0.0686 *		
1.68	0.66	-1.22		*-1.74*		
-0.0017	0.0365 **	-0.0008			0.0463 ***	
-0.37	1.91	-0.15			3.23	
Panel D. Liu (LM12)						
0.0005	0.0004 **	1.0306				0.0003
0.11	1.73	0.64				0.49
0.0005	0.0003 **	1.0248	0.0003			
0.11	1.67	0.64	0.56			
0.0023	0.0002 *	1.0022		-0.2582		
0.48	1.56	0.57		-1.48		
-0.0010	-0.0002	1.5138			0.1683 ***	
-0.21	-0.68	0.93			4.20	
Panel E. Lesmond et al. (LOT)						
0.0009	0.7722 ***	-0.0012				-0.1474
0.21	3.40	-0.18				-1.36
-0.0003	0.7419 ***	-0.0008	-1.6060 **			
-0.07	3.07	-0.17	-2.51			
0.0069	0.5568 ***	-0.0100		-0.1375		
1.49	2.35	-1.56		-0.76		
0.0027	0.7738 ***	-0.0042			0.2415 *	
0.64	3.32	-0.82			*1.77*	
Panel F. Roll (RO)						
0.0024	0.5278 ***	-0.0064				0.0298
0.53	2.94	-1.04				0.37
0.0056	0.3504 **	0.0117 **	-4.4837 ***			
1.19	2.05	2.27	-5.81			
0.0129 **	0.3534 **	-0.0235 ***		-0.4630 ***		
2.53	2.09	-3.19		-3.31		
0.0043	0.4981 ***	-0.0016			0.2672 **	
0.89	2.82	-0.31			2.32	
Panel G. Corwin and Schultz (CS)						
-0.0008	0.4775 *	0.0087				0.3071 *
-0.15	1.43	1.26				1.93
-0.0120 **	0.3751	0.0270 ***	-17.8921 ***			
-2.24	1.04	3.89	-4.82			
-0.0035	0.3859	0.0134 *		-0.8968 ***		
-0.64	1.15	1.83		-2.61		
0.0004	0.6181 **	0.0063			-0.3626 *	
0.08	1.87	1.00			-1.77	
Panel H. Goyenko et al. (ET)						
-0.0177 ***	0.4913 ***	0.0268 ***				-0.3251 ***
-3.26	4.91	4.31				-4.96
-0.0119 **	0.5498 ***	0.0172 ***	-5.4802 ***			
-2.34	4.79	3.07	-4.47			
-0.0128 **	0.3959 ***	0.022 ***		0.3809 *		
-2.32	3.15	3.07		1.85		
-0.0115 **	0.3841 ***	0.0174 ***			0.4687 ***	
-2.17	4.35	3.00			5.61	

Table A2
Cross-sectional regressions using 25 illiquidity portfolios as test assets.
We form 25 illiquidity portfolios for each year, based on the average of stock illiquidity over the previous year using 2,762 stocks. For each portfolio *i*, we estimate the beta *k* (k=1,…,4) using the monthly returns and innovations of illiquidity over the sample period. Market aggregate illiquidity and portfolio illiquidity are formed by taking an equally weighted average of stock illiquidity. With all four betas obtained by repeating this procedure for all k, we compute the liquidity net beta, Beta 5, as in Eq. (4). We perform the following cross-sectional regressions for each month using portfolio returns and estimated betas.

$$E\left(R_{i,t}-R_{f,t}\right) = a + bE(C_{i,t}) + \lambda_1\hat{\beta}^1_{i,t} + \lambda_2\hat{\beta}^2_{i,t} + \lambda_3\hat{\beta}^3_{i,t} + \lambda_4\hat{\beta}^4_{i,t}$$

The table shows the time-series averages of the estimated coefficients together with the *t*-values in italics. The illiquidity measures we use are Amihud's measure (2002; *RV*), Pástor and Stambaugh's measure (2003; *PS*), the zero-return measure *(ZR)*, Liu's measure (2006; *LM12*), the illiquidity measure of Lesmond, Ogden, and Trzcinka (1999; *LOT*), Roll's measure (1984; RO), the spread estimates of Corwin and Schultz (2012; CS), and Goyenko, Holden and Trzcinka's effective tick (2009; ET). *Illiq* is the previous 12 months' average of a given illiquidity measure. *Illiq* is tested against the alternative hypothesis of positive coefficients, while the others are two-tailed tests. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Intercept	Illiq	Beta1	Beta2	Beta3	Beta4	Beta5
Panel A. Amihud measure (RV)						
-0.0001	-0.0081	0.3011				0.0013
-0.02	-0.79	0.71				1.46
-0.0006	-0.0048	0.3401	0.0009			
-0.11	-0.45	0.79	1.03			
-0.0001	0.0049 ***	0.2843		-0.0066		
-0.01	2.82	0.60		-0.09		
-0.0019	0.0078 ***	0.4410			0.0231	
-0.39	3.57	1.10			0.95	
Panel B. Pástor and Stambaugh (PS)						
-0.0088	0.0322 *	0.0082				0.0033
-1.25	1.55	1.37				0.43
-0.0067	0.0295 *	0.0066	-0.0006			
-0.79	1.37	0.97	-0.03			
-0.0108	0.0336 *	0.0103 *		-0.0143		
-1.56	1.63	1.70		-0.41		
-0.0079	0.0272 *	0.0075			-0.0037	
-1.15	1.34	1.28			-0.43	
Panel C. Zero return (ZR)						
0.0000	-0.0088	0.0093 **				-0.0923
0.00	-0.04	2.25				-0.99
0.0005	-0.0857	0.0062	0.5223			
0.23	-0.40	1.42	0.46			
-0.0015	0.0083	0.0167 ***		0.5732 **		
-0.68	0.04	3.00		2.22		
0.0002	-0.0514	0.0073 *			0.0088	
0.08	-0.23	1.85			0.08	
Panel D. Liu (LM12)						
0.0094 ***	0.3096 **	-0.0043				-0.0428
2.70	1.69	-0.90				-0.25
0.0098 ***	0.3510 **	-0.0002	-6.5829			
2.92	1.85	-0.05	-1.31			
0.0085 **	0.3193 **	-0.0021		-0.1325		
2.56	1.74	-0.47		-0.40		
0.0094 ***	0.3073 **	-0.0044			0.0992	
2.75	1.67	-1.02			0.53	
Panel E. Lesmond et al. (LOT)						
-0.0046	-0.0216	0.0194 *				0.0019 ***
-1.01	-0.40	1.76				3.87
-0.0048	-0.0239	0.0205 *	0.0025 ***			
-1.05	-0.47	1.83	3.95			
-0.0026	-0.0509	0.0016		-0.0580 **		
-0.59	-1.14	0.16		-2.28		
-0.0031	-0.0278	0.0167			-0.0085 ***	
-0.72	-0.45	1.58			-3.72	
Panel F. Roll (RO)						
0.0095 ***	0.0004 ***	-1.1220				-0.0010 **
3.82	3.58	-1.43				-2.24
0.0095 ***	0.0004 ***	-1.1188	-0.0010 **			
3.82	3.56	-1.43	-2.22			
0.0095 ***	0.0002 ***	-1.4504 *		0.1936		

Table A2 (*continued*)

Intercept	Illiq	Beta1	Beta2	Beta3	Beta4	Beta5
3.84	2.95	-1.70		1.20		
0.0094 ***	0.0000	-1.1105			0.0651	
3.72	0.02	-1.37			0.93	
Panel G. Corwin and Schultz (CS)						
0.0034 *	-0.1831	-0.0022				0.1613 *
1.74	-0.95	-0.40				1.90
0.0045 **	-0.2003	0.0046	-0.0055			
2.11	-1.04	1.00	-0.01			
0.0048 **	-0.1497	-0.0011		-0.1966		
2.53	-0.76	-0.17		-1.13		
0.0036 *	-0.2425	0.0039			-0.1217	
1.82	-1.25	0.88			-1.49	
Panel H. Goyenko et al. (ET)						
-0.0076	0.1111 **	0.0146 **				-0.0930 *
-1.15	1.72	2.02				-1.94
-0.0098	0.1907 ***	0.0155 **	-2.6970 ***			
-1.42	2.41	2.11	-2.85			
-0.0004	0.0547	0.0060		-0.0185		
-0.06	0.61	0.69		-0.08		
-0.0049	0.0964 *	0.0109			0.1261 **	
-0.75	1.46	1.56			2.08	

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