Liquidity in asset pricing: New evidence using low frequency data

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Abstract

Employing a new proxy for liquidity, this paper examines its impact on stock returns in the context of the Fama-French framework. We augment the Carhart four-factor model with a liquidity factor and employ individual and system regression techniques. Using an extensive dataset drawn from the Australian equities market, we find a significant illiquidity premium and evidence that liquidity explains a portion of the common variation in stock returns even after controlling for size, book-to-market and momentum. However, our findings suggest that the liquidity factor only adds marginal explanatory power to contemporary asset pricing models.

Keywords Liquidity; Asset pricing; Fama-French model; Australian evidence

EFM classification 310, 350

JEL classification G12

1. Introduction

The central purpose of this study is to examine the impact of liquidity on the generation of stock returns using stocks listed on the Australian Securities Exchange (ASX). The ASX trading mechanism is different from that of the US market primarily because of the absence of the market makers and the fact that public limit orders provide liquidity to the market and establish the bid and ask prices. This characteristic produces a more transparent trading environment in that market participants have the ability to observe recent trades. Brown and Zhang (1997) also point out that markets that allow limit orders tend to have a lower execution-price risk and have a higher level of liquidity. The order-driven setting of the Australian market provides us an opportunity to further explore the well-documented relationship between liquidity and stock returns. Accordingly, there are four related aims in this study. First, we extend prior Australian research by employing a much longer and richer sample, which enables us to conduct a more powerful asset pricing test that will help reconcile the mixed findings. Our sample period extends for a quarter of a century (1982-2006). Second, we adopt a new and enhanced proxy for illiquidity, thus providing an innovation of how illiquidity can be measured. Third, our asset pricing tests are performed in the context of the Fama-French framework and involve the construction of a liquidity mimicking portfolio. Fourth, we investigate the importance of liquidity in the presence of variables that are known to affect stock returns (i.e. beta, size, book-to-market and momentum).

The seminal work of Amihud and Mendelson (1986) formalizes the link between stock returns and stock liquidity. They suggest that investors with a longer holding period require a higher compensation for illiquidity as reflected in the bid-ask spread (the clientele effect). Over the ensuing years, there has been growing interest in the importance of the relationship between liquidity and stock returns. Earlier studies such as Eleswarapu and Reinganum (1993) and Brennan and Subrahmanyam (1996) use bid-ask spreads and other microstructure variables to measure illiquidity. Later studies such as Brennan, Chordia and Subrahmanyam (1998); Datar, Naik and Radcliffe (1998); Chordia, Subrahmanyam and Anshuman (2001); Amihud (2002); Pastor and Stambaugh (2003); Lesmond (2005); Liu (2006); Bekaert, Harvey and Lundbald (2007); and Keene and Peterson (2007) use proxies other than bid-ask spreads and microstructure measures. The expanded focus on alternative proxies is in part due to the fact that Brennan and Subrahmanyam (1996) did not find reliable evidence that bid-ask spreads were related to stock returns and also the difficulty of obtaining such data over long time periods. The search for alternative proxies also highlights the contention that liquidity involves a number of dimensions and it is doubtful that a single measure can capture all its aspects (Kyle, 1985; Amihud, 2002)

Lo and MacKinlay (1990) contend that asset pricing tests need to be examined with alternative datasets to avoid data snooping bias. In response to this view, a handful of studies have examined the role of liquidity in asset pricing in the Australian market with mixed results. Chan and Faff (2005) and Limkriangkrai, Durand and Watson (2008) find strong support for a liquidity-augmented Fama-French model and evidence that liquidity plays an important role in asset pricing. Chan and Faff (2003) also document a strong cross-sectional relationship between liquidity and stock returns. In contrast, Anderson, Clarkson and Moran (1997), Marshall and Young (2003) and Gharghori, Chan and Faff (2007) do not find strong evidence that liquidity is related to stock returns. It is noteworthy that the prior Australian studies mainly use volume-based measures as a proxy for liquidity. Surprisingly, different conclusions were obtained even when similar liquidity proxies were employed. A likely (partial) explanation for this divergence is that these studies cover different samples of the entire population of stocks and relatively short time periods. It is also possible that the liquidity proxies employed by these studies will capture other effects. Thus, whether liquidity risk is priced in stock returns remains an open question in the Australian market.

The remainder of this paper continues as follows. Section 2 introduces the new illiquidity measure. Section 3 outlines the empirical method. Section 4 describes the data sources, the construction of the factors and the dependent variable portfolios. Section 5 discusses the results and Section 6 concludes.

2. Measuring illiquidity

Liquidity is multidimensional. It is not directly observable and involves a number of dimensions that cannot be fully captured in a single measure (Kyle, 1985). Most of the illiquidity (liquidity) measures used in asset pricing tests are constructed from daily share price information. Part of the reason is that such information is easier to obtain in most markets around the world over long timeframes, particularly in comparison to intraday data. In contrast, the illiquidity measure used in this study is obtained from stocks' monthly trading characteristics: stock price, absolute monthly stock return and the thin trading measure proposed by Beedles et al. (1988) (hereafter BEEDLES).

We use monthly trading characteristics for two reasons. First, in Australia, daily price information is limited to a subset of stocks after 1990 and such data are not reliable prior to 1990. This data limitation motivates us to seek alternative proxies using reliable and comprehensive data sources. Second, trading characteristics such as stock price, trading volume and volatility have been shown to be significant determinants of liquidity (e.g. see Stoll, 2000; Chordia, Roll and Subrahmanyam, 2000). Further, monthly trading characteristics are readily accessible and thus, they are potentially able to fulfil our purpose of creating a new illiquidity measure.

We define illiquidity (hereafter IM) of a stock as the summation of the standardised measures of three monthly trading characteristics:[1]

$$IM_{jt} = \left(1/PRICE_{jt} \right)^{S} + ABSR_{jt}^{S} + BEEDLES_{jt}^{S} \tag{1}$$

where PRICE is the month end price for stock j in month t, ABSR is the absolute monthly stock return for stock j in month t, BEEDLES is the thin trading measure proposed by Beedles et al. (1988) for stock j in month t.[2] The superscript 'S' indicates standardized variables. The standardization is achieved as follows:

$$standardization = \frac{variable_{jt} - mean_t}{\sigma_t} \tag{2}$$

where 'variable' is a given trading characteristic (i.e. 1/PRICE, ABSR or BEEDLES) for stock j in month t, 'mean' is the sample cross-sectional mean of the variable in month t, and σ is the sample cross-sectional standard deviation of the variable in month t. The standardization process converts each measure to have zero cross-sectional sample mean and unit cross-sectional sample variance. As such, this makes each variable comparable and, thus,

[1] Each of the three sub-measures in our analysis is an imperfect proxy for different dimensions of liquidity. Since liquidity is multidimensional, it is difficult to justify which characteristic is more important. Further, assigning an equal weight to each standardized sub-measure ensures that IM is not heavily influenced by a particular characteristic. And, it is important to note that we standardize each sub-measure – such standardization from a statistical point of view will have the effect of placing them on an equal footing. Nevertheless, we conduct a robustness check on the validity of our construction method. Specifically, instead of giving equal weights, the importance of each sub-measure is determined by functions that best describe commonality in liquidity. In our setting, we use Principle Component Analysis (PCA) to obtain a common liquidity factor out of a set of illiquidity proxies. The dominant liquidity factor produced by the PCA is then regressed on the three sub-measures. We then construct an alternative proxy based on the estimated regression coefficients. The output of this approach is quite similar to that generated from Equation 1. For example, this alternative proxy is highly correlated with IM (exceeding 0.8 in cross-section) and reacts very similarly to variables such as firm size, B/M and momentum. The results are available from the authors upon request.

[2] We do not include other potential characteristics such as trading volume and volatility of daily stock returns since they are subject to substantial data limitations.

IM should not be heavily influenced by any particular trading characteristic – it should be an amalgam measure that captures the core essence across the three components. Table 1 displays descriptive statistics for the three 'standardised' sub-measures over the period where IM was constructed. As expected, each standardised sub-measure has zero cross-sectional mean and unit cross-sectional sample variance. Looking at the distribution closely, both 1/PRICE and BEEDLES have higher skewness, and there is a large gap between upper quartile and maximum values. These results are not surprising since some stocks in our sample have prices below 10 cents. Also, stocks that exhibit serious non-trading problems will have high BEEDLES values. Thus, the IM measure should have a distribution that takes both positive and negative values.

[Insert Table 1 about here]

The rationale for including PRICE and ABSR is based on order processing and inventory considerations (Stoll, 2000; Chordia et al., 2000). Stoll (1978) develops a theoretical model to estimate the total cost of dealer services.[3] In his model, given the same total cost of trading, higher priced stocks have a relatively lower order processing cost. Further, empirical evidence shows that the percentage spread increases as the price of a stock decreases (e.g. Demsetz, 1968; Branch and Freed, 1977). This is because transaction costs are proportionately higher for the smaller dollar value of trades in low price stocks.[4] Stock price also controls for the effect of discreteness and low price stocks tend to be riskier (Stoll, 1978; 2000). As a result, low price stocks are generally less liquid than high price stocks. Accordingly, the reciprocal of price in equation (1) can be regarded as an indication of trading costs.[5]

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[3] The total cost of dealer services involves three types of costs - holding costs, order costs and information costs.

[4] Australian evidence on the relationship between the spreads and stock price levels has been documented in Aitken and Frino (1996). Stoll (1978) and McInish and Wood (1992) point out the 1/8 minimum tick rule on the US exchanges may cause lower priced stocks to have relatively higher spreads. There are analogous price variation rules on the Australia Securities Exchange (ASX). The ASX currently has three different minimum price steps when trading stocks: the tick size is $0.001 for stocks priced below $0.1, $0.005 for stocks priced from $0.1 to $0.5, and $0.01 for stocks priced $0.5 and above (http://www.asx.com.au). The rules determine the minimum bid-ask spread at which an order can be executed at different price levels. It can be seen that the current ASX tick size rule may result in large minimum percentage spreads for low priced stocks. Therefore, low priced stocks have relatively higher transaction costs (lower liquidity).

[5] A firm's stock price is also related to its market capitalization. Thus, it is possible that IM captures a portion of the size effect. However, Australian evidence by Gaunt, Gray and McIvor (2000) shows that firm size and share price have significant and independent effects on portfolio returns. In addition, as will be discussed later, we control for firm size when estimating the illiquidity premium.

Absolute monthly stock return is regarded as an alternative measure of volatility and may be used as a proxy for information flow.[6] Compared to conventional volatility measures, it is easier to calculate and the data requirements are less onerous. The inventory explanation predicts that higher volatility increases the risk of holding inventory and it leads to widening of spreads (Stoll, 1978; Tinic, 1972). Therefore, a positive relationship between an asset's volatility and illiquidity is expected. Moreover, an information asymmetry explanation also predicts such a relationship (Foster and Viswanathan, 1990). They show that the volatility of price changes and trading costs are highest when information asymmetry is high. As a result, liquidity is low at times of high volatility. Finally, a stock's return volatility is related to its depth. Specifically, stocks with greater depth normally have less return volatility (e.g. Ahn, Bae and Chan, 2001).

Beedles et al. (1988) create a proxy of thinness based on the difference between the last price date and the last trading date (n) of securities in the CRIF database of Australian stocks, which can be formulated as:

$$\text{BEEDLES} = \{100-[100/(n+1)]\}/100 \tag{3}$$

In their setting, if a stock is traded on the last trading date of the month (n = 0), it is presumed that the stock traded everyday (0% of non-trading). If a stock is traded on the second last trading day (n = 1), it is presumed that the stock traded every second day (50% of non-trading). Thus, the value of BEEDLES ranges from zero to one. A value of zero implies that a stock trades every day in a particular month. However, as noted in Beedles et al. (1988), this measure is not an ideal proxy for illiquidity. It is possible that a stock has no difference between the last price date and the last trading date in a month throughout its trading history. Nevertheless, using this measure, they find that small size portfolios have a larger proportion of non-trading, indicating that small stocks are less liquid. BEEDLES aims to capture the thin trading aspect of stock illiquidity and thus, it should be positively related with illiquidity.[7]

To demonstrate the empirical relevance of the three sub-measures, we examine correlations among them and also their correlations with various illiquidity measures commonly used in the literature. The measures include the proportional bid-ask spread (hereafter PBA); the illiquidity ratio from Amihud (2002) (hereafter AMIHUD); the return reversal measure from Pastor and Stambaugh (2003); the proportion of zero daily returns

[6] The idea is similar to that used in Duffee (1995), Ding, Granger and Engle (1993) and Chordia, Shivakumar and Subrahmanyam (2004).

[7] Ideally, the thin-trading aspect of liquidity is better captured by the number of zero-return or zero-trading days in a month. However, as mentioned before, daily price information is not readily available over our sample period, and hence, we utilise BEEDLES as an alternative viable proxy for thin trading.

from Lesmond, Ogden and Trzcinka (1999) (hereafter ZERO); stock turnover (hereafter TO), and the turnover-adjusted zero daily volumes from Liu (2006) (hereafter LIU).[8] Each of these measures captures a different dimension of illiquidity and they are widely used in the asset pricing literature. Both PBA and ZERO capture tightness since both proxies reflect trading costs; both AMIHUD and PS represent the price movement associated with trading volume and therefore it is related to price impact (depth); both TO and LIU represent immediacy because both proxies reflect trading speed and trading frequency. For consistency purposes and ease of interpretation, we flip the sign of the return reversal measure and stock turnover to make them represent illiquidity. Most of these measures require daily price information. Given data constraints, the test sample is restricted to the period from January 1991 to September 2006 and only to those stocks that have daily price information.

Table 2 displays the average monthly cross-sectional correlations between the three sub-measures and illiquidity measures.[9] The correlations among the three sub-measures are generally low. As expected, PRICE is negatively correlated with ABSR and the correlation tends to be relatively stronger compared to other results.[10] In regard to their relationships with the illiquidity measures, the results show that PRICE is negatively correlated with PBA, ZERO and LIU. The results imply that high-priced stocks have relatively lower transaction costs (PBA and ZERO) and lower frequency of non-trading (ZERO and LIU). These results are as anticipated since stock price is expected to somehow reflect transaction costs and other considerations like inventories (Stoll and Whaley, 1983). The correlations between ABSR and the illiquidity measures are less apparent. There is weak evidence that ABSR is correlated with PBA and TO. The negative relationship between ABSR and TO looks odd at first glance, but we suspect that this result is driven by firm size. The relationship between firm size and share turnover is found to be negative and close to zero in Australia (e.g. see Chan and Faff, 2003). A close investigation (not reported) shows that small firms have higher share turnover than medium-size and large firms. This finding partially explains the negative relationship found between ABSR and TO. BEEDLES is expected to be positively related with illiquidity since it is a proxy for thin trading. The results show that BEEDLES is

[8] See the Appendix for the definition of these measures.
[9] A more direct approach to demonstrate the empirical relevance of the three sub-measures in capturing illiquidity is to run cross-sectional regressions with illiquidity measures regressed on the three sub-measures. We find that the influences of the three sub-measures are generally consistent with our expectations and their impacts are large and highly significant. Moreover, we find some evidence that they are related with stock returns. The results are available from the authors upon request.
[10] As a robustness check, we also look at the correlations of the three sub-measures over our full sample period from January 1982 to December 2006. The results are similar to those reported in Table 2.

positively related with PS, PBA, ZERO and LIU. Given the trading aspect that BEEDLES aims to capture, it is not surprising that BEEDLES is related to ZERO and LIU, which both of these measures consider non-synchronous trading.

Initially, to demonstrate the usefulness of IM, it is important to compare it with a wider range of potential illiquidity (liquidity) measures that are more data intensive. To achieve this, we assess the cross-sectional correlations between IM and the six illiquidity measures discussed above. Recently, Goyenko, Holden and Trzcinka (2009) demonstrate that illiquidity (liquidity) proxies constructed from low-frequency data (daily) are comparable to high-frequency (intraday) measures. This gives us some confidence on the usefulness of these proxies in capturing illiquidity. The results show that IM is quite strongly correlated with PBA, LIU and ZERO. Notably, both PBA and ZERO aim to capture trading costs. The idea of the number of zero daily trading volumes in LM is also similar to ZERO. Since IM reflects part of the trading cost, it is not surprising that IM is correlated with these three measures. However, IM is not related to AMIHUD and TO. This result could be due to data limitations, in that IM does not take trading volume into consideration. It should be noted that these measures of illiquidity as well as the new illiquidity measure proposed in this study can be regarded as empirical proxies that capture different aspects of illiquidity. It is doubtful that a single proxy can captures all its aspects. Overall, the results from Table 2 give us some confidence about the usefulness of IM as an illiquidity measure.

[Insert Table 2 about here]

3. Research method

3.1 Cross-sectional relationship between illiquidity and stock returns

To examine the effect of illiquidity on stock returns, we run cross-sectional regressions where monthly stock returns are a function of stock characteristics:

$$R_{jt+1} = \alpha_t + \sum_{k=1}^{K} \beta_{kt} X_{jkt} + \varepsilon_{jt} \tag{4}$$

where j = 1,2,…,N; t = 1,2,…,T; R_{jt+1} is the return on stock j in month t+1; X_{jkt} represents each firm characteristic variable such as IM, firm size, B/M and price momentum. This means we run T regressions, each one using N observations. The test procedure follows the usual Fama and MacBeth (1973) method. The method involves three stages. In stage one, the dependent variable (individual stock return) and independent variables (firm characteristics) required for the cross-sectional regression are constructed. We then estimate different versions of equation (4) using OLS each month from January 1982 to December 2006 in stage two. In stage three, we compute the average coefficient and variance from the time series of the cross-sectional regression coefficients generated in stage two.

3.2 Asset pricing tests

Our primary empirical model is the Carhart (1997) four-factor model augmented by a liquidity factor:

$$RP_{jt} - RF_t = a_j + b_j[RM_t - RF_t] + s_j SMB_t + h_j HML_t + m_j MOM_t + i_j IML_t + e_{jt} \quad (5)$$

where *RP* is the value-weighted return for portfolio j, *RF* is the monthly risk-free rate; RM is the value-weighted market monthly return; SMB, HML, MOM and IML are the factor-mimicking portfolios for size, book-to-market, momentum and liquidity.[11] While there are a number of different ways to test the time-series implications of the five-factor model, this study employs the Generalised Method of Moments (GMM) technique. In the GMM setting, moment conditions are required. For the five-factor model, the moment conditions are: (a) the mean regression error term is zero; and the regression error term is orthogonal to each independent variable, namely, (b) RM_t-RF_t; (c) SMB_t; (d) HML_t; (e) MOM_t; and (f) IML_t. This gives us *6N* sample moment conditions, the system is just identified and the estimated parameters are equivalent to their Ordinary Least Squares (OLS) counterparts.

We are interested in the extent to which the IML factor[12] can enhance the model's explanatory power of the variation in stock returns. If the intercepts of equation (5) are jointly equal to zero, then the asset pricing model as specified is able to explain stock returns after controlling for liquidity. To test this we can impose a restriction on the five-factor model that α_j = 0. The restricted version of the five-factor model is then:

[11] As will be explained shortly, the liquidity mimicking portfolio is obtained by calculating the difference between the average return of the least liquid portfolios (I) and the average return of the most liquid portfolios (L), therefore the term IML (Illiquid Minus Liquid).

[12] It is possible that IML is influenced by variables that are known to affect stock returns. To ensure that our results are robust, we also consider an orthogonolized liquidity factor. That is, we purge the effects associated with the market, size, book-to-market and momentum by regressing IML on the market excess return and factor mimicking portfolios of size, book-to-market and momentum. The orthogonolized liquidity factor is the sum of the regression intercept and the regression residuals. The results are similar and are available upon request from the authors.

$$RP_{jt} - RF_t = b_j[RM_t - RF_t] + s_j SMB_t + h_j HML_t + m_j MOM_t + i_j IML_t + e_{jt} \qquad (6)$$

This restriction can be tested by forming the following D-statistic (Newey and West, 1987) which has a χ^2 distribution:

$$Tg_T(\hat{\phi}_R)'.S_T^{-1}.g_T(\hat{\phi}_R) - Tg_T(\hat{\phi}_U)'.S_T^{-1}.g_T(\hat{\phi}_U) \sim \chi^2_{6N} \qquad (7)$$

where $g_T(\hat{\phi}_R)$ and $g_T(\hat{\phi}_U)$ are the empirical moment condition vectors for the restricted and unrestricted models, respectively, S_T^{-1} is the optimal weighting matrix and T is the number of time series observations.[13]

Finally, we compare the performance of equation (5) and the Carhart four-factor model in explaining returns on the test portfolios created. The counterpart four-factor empirical model is:

$$RP_{jt} - RF_t = a_j + b_j[RM_t - RF_t] + s_j SMB_t + h_j HML_t + m_j MOM_t + e_{jt} \qquad (8)$$

We assess the explanatory power of equations (5) and (8) by comparing their adjusted R^2s and the statistical significance of the regression intercepts. The GMM setting similar to equation (5) will also apply to equation (8).

4. Data, cross-sectional analysis and portfolio formation

4.1 Data sources

Our asset pricing tests are conducted for stocks traded on the Australian Securities Exchange (ASX) at the monthly level from January 1982 to December 2006. The data comprises monthly share price information and annual accounting information. Share price information

[13] As a robustness check, we also perform the test developed by Gibbon, Ross, and Shanken (1989) (GRS) to test the restriction on the intercepts. The GRS F-statistics is computed as:

$$\left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}}\right] \sim F(N, T-N-L)$$

where T is the number of observations, N is the number of regressions in the system, L is the number of explanatory variables in the regression, $\hat{\alpha}$ is a Nx1 vector of estimated intercepts, $\sum$ is the residual covariance matrix, $\bar{\mu}$ is the Lx1 vector of the explanatory variables' sample means, and Ω is the covariance matrix of the explanatory variables.

is obtained from the Centre for Research in Finance (CRIF) database, which includes monthly share prices, stock returns, market capitalizations, returns on the value-weighted market index and on the 13-week Treasury note, and the trading characteristics that are required to calculate IM. The accounting items required to calculate the book-to-market ratio are hand collected from company annual reports over the sample period. Accounting items include total shareholder's equity, outside equity interests, preference shares and future tax benefits. Following Fama and French (1993), we define book value of equity as total shareholder's equity minus the value of preference shares, outside equity interests and future fax benefits. The book-to-market ratio of year t+1 is calculated in December of year t as Australia has a June financial year end. This approach creates a similar time window to that of the counterpart US studies. We exclude negative book-to-market stocks in tests that involve book-to-market. Further, companies must have traded in month t when portfolio formation takes place to ensure that a reliable measure of market capitalization is obtained. Companies must also not be delisted prior to the formation period.

Table 3 presents summary statistics for the variables used in this study, which includes IM, size, book-to-market and the cumulative return over the 12 months ending at the beginning of the previous month (i.e. momentum).[14] Panel A shows the results over the full sample period (January 1982 – December 2006). As expected, given the statistics in Table 1, IM is well dispersed and has a wide range of values either side of zero. The minimum value is -1.91 and the maximum is 15.47. The lower the IM value, the lower the level of illiquidity. The negative median indicates that over half of our sample stocks exhibit a negative value of IM. Moreover, its standard deviation, kurtosis and skewness are generally lower compared to the other variables.

Size, book-to-market and momentum are also well dispersed. The size variable exhibits a large standard deviation. The maximum, median and minimum values show that the size distribution is non-normal. Further, a comparison of the mean, maximum and quartile size values indicates that the majority of the firms are relatively small. The cross-sectional Spearman rank correlations show that IM is not correlated with the book-to-market ratio and momentum, which will give us confidence that IM is not picking up the book-to-market and momentum effects. IM is negatively correlated with size (-0.59) suggesting that small firms are less liquid. This relation is expected since size could be a reasonable proxy for liquidity. Moreover, we find that the correlations among size, book-to-market and

[14] The past twelve-month return with a one month lag is used to construct the Carhart (1997) momentum factor.

stocks' past performance are generally low, which are quite similar to those found in Chan and Faff (2003).[15] The results from the sub-period analysis (Panel B and Panel C) are similar to those in Panel A, especially the correlations. These results imply that the variables used in this study are comparable over time.

[Insert Table 3 about here]

4.2 Cross-sectional analysis

Before discussing our main asset pricing tests, it is important to show how IM is related to stock returns. In each month from January 1982 to December 2006, we run cross-sectional regressions of next month's stock returns, both individually and jointly, on our illiquidity measure IM and firm characteristic variables such as size, book-to-market and momentum.[16] We use the conventional Fama-MacBeth method to estimate the time series average of the cross-sectional slope coefficients. Table 4 summaries the results of estimating nine alternative regression specifications. The major finding of note from the univariate regressions (regressions 1 to 4) is that IM is significant and positively related to stock returns. Size and book-to-market are also related to stock returns and the sign of coefficients on these variables are as expected. Momentum, on the other hand, does not show any explanatory power.

The results of multivariate regressions are presented in regressions 5, 6, 7, 8 and 9. The aim of these regressions is to understand how IM describes average stock returns after controlling for size, book-to-market and momentum. Regressions 5, 6 and 7 of Table 4 show that when each of the size, book-to-market and momentum variables is regressed together with IM, the explanatory power of IM remains. Given the high correlation between IM and size (Table 3), it is likely that size may subsume the role of IM. However, the average slope on IM remains high and statistically significant even when size is presented. The final two regressions we report from Table 4 (regressions 8 and 9) are the following month's returns on most and then all the variables used in the analysis. We observe that IM, size and book-to-market retain their characteristics from the univariate regressions. The momentum variable becomes statistically significant in the multivariate regressions. Nonetheless, the results from Table 4 show that IM consistently displays a high level of significance after controlling for size, book-to-market and momentum.

[15] In Chan and Faff (2003), based on a sample period from 1990 to 1999, the correlation is -0.193 between book-to-market and size, -0.057 between book-to-market and past six-month returns, and 0.052 between size and past six-month returns.

[16] Since some variables are highly skewed (e.g. size), we winsorized the variables before they are used in the cross-sectional regressions. That is, we change the extreme values of each variable to its 95th and 5th percentile values. The un-winsorized results are similar to that in Table 4.

[Insert Table 4 about here]

4.3 Construction of the mimicking portfolios

For the SMB and HML factors, following Fama and French (1993), we form six portfolios from the intersections of two size and three book-to-market portfolios. At the end of December of year t, we first rank stocks according to their market capitalization and the median market capitalization is used to split stocks into two groups, small and big. We then rank stocks based on their book-to-market ratio and separate them based on the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high). Monthly value-weighted returns on the six portfolios are calculated from January to December of year t+1. The portfolios are reformed each December. SMB (Small Minus Big) is the average return on the three small size portfolios minus the average return on the three big size portfolios. Similarly, HML (High Minus Low) is the average return on the two high book-to-market portfolios minus the average return on the two low book-to-market portfolios.

The construction of the momentum factor (MOM) follows Carhart (1997). In each month, we calculate the cumulative return over the past 12 months with a one month lag (month t-2 to month t-12). Stocks are then sorted into three portfolios based on their past performance using a 30-40-30 split. MOM is the difference between the equally-weighted return on the portfolio of firms with the highest 30 percent past returns and the equally-weighted return on the portfolio of firms with the lowest 30 percent past returns. The momentum portfolios are rebalanced on a monthly basis.

The liquidity mimicking portfolio, IML, is constructed as follows. In order to construct a liquidity mimicking portfolio that is not too heavily influenced by firm size, we form portfolios double sorted on size and IM in a manner similar to the six size and book-to-market portfolios used in Fama and French (1993). Specifically, we independently sort all available stocks into two size groups (based on a 50%: 50% partition) and three liquidity groups (based on a 30%: 40%: 30% partition), yielding six portfolios from the intersection of the size and liquidity groups.

An important methodological consideration that arises is how often should portfolios be held or updated. We argue that the illiquidity effect should be observed quickly in stock returns. For example, stock returns in the current month should reflect the level of illiquidity in the previous month. Thus, in this paper, portfolios that involve IM are formed and updated on a monthly basis. This approach allows stocks to move between portfolios when their characteristics change. Unlike yearly rebalancing, which keeps a stock in a particular portfolio for twelve months, we argue that monthly rebalancing would best reflect the relationship between liquidity and stock returns.[17]

As discussed above, the six size and IM portfolios are formed at month t and the value-weighted returns are calculated in month t+1. The liquidity mimicking portfolio (IML, Illiquid Minus Liquid) is obtained by calculating the difference between the simple average of returns from the two least liquid portfolios and the simple average of returns from the two most liquid portfolios. To investigate whether the illiquidity premium is special to a particular size group, we partition IML into its small stock and big stock components. The small (big) stock component, IMLS (IMLB), is the difference between the return of the least liquid portfolio and the return of the most liquid portfolio in small (big) size portfolios.

Table 5 presents summary statistics for the factor portfolios used in the analysis. Panel A presents the results for the full sample period. The average market risk premium is positive and is about 0.4% per month. The SMB and HML returns are significantly positive with an average premium of 3.21% (t = 8.45) and 0.65% (t = 2.68) per month, respectively. Compared to SMB and HML, the return on MOM is less prominent and is 0.53% per month. There is a clear and significant illiquidity premium (IML) of 1.98% (t = 6.55) per month. Looking at the IMLS and IMLB returns, the IMLS return for the full sample period is 4.09% (t = 8.47) per month, while IMLB exhibits a negligible average return (-0.13% per month, t = -0.4). This result suggests that the illiquidity effect is more pronounced in small stocks, which is intuitively appealing.

Brown, Keim, Kleidon and Marsh (1983) find that January and July exhibit higher returns in Australia. To check that the results above are not driven by seasonality, we re-examine the returns when January and July are excluded. Panel B presents the results. The portfolio returns are generally smaller compared to those in Panel A – this indicates that these two months exhibit higher returns on average than the remaining months. However, in each case the mean return of SMB, HML and IML is still significantly positive. This suggests that the size, book-to-market and illiquidity premiums are not confined to January and July. Moreover, similar to the results in Panel A, only IMLS is statistically significant (3.13% per month, t = 6.42).

[17] This approach is consistent with prior Australian studies. Limkriangkrai et al. (2008) form liquidity portfolios on a monthly basis with three different return holding periods, namely one, three and six-months. They find that the returns are similar across different horizons. In the US market, Amihud (2002) finds that the relationship between liquidity and stock returns is robust when liquidity is measured either monthly or annually.

To ensure that the results in Panel A are not period specific, we divide the full sample period into two sub-periods – namely, January 1982 to December 1993 and January 1994 to December 2006. Panels C and D display the results. The SMB premium is quite stable across the sub-periods. The HML, IML and IMLS premiums tend to be stronger in the first half of the sample period; however, there is no strong evidence that the return premiums are different across the sub-periods. The momentum effect is more pronounced in the second half of the sample period. Overall, the results in Table 5 suggest that there is an illiquidity premium in the Australian equity market, which is concentrated in small firms.

[Insert Table 5 about here]

4.4 Construction of the dependent variables

In the spirit of Fama and French (1993), we form 25 size and IM portfolios and use them as the dependent variables in the time-series regressions.[18] The purpose is to test whether our liquidity factor, IML, can capture cross-sectional variation in stock returns related to liquidity. In each month t, stocks are first ranked by market capitalization and divided into quintiles. Independently, similar to the size sort, stocks are ranked by IM and divided into quintiles. Twenty-five portfolios are constructed from the intersection of the size and IM quintile sorts and value-weighted returns on these 25 portfolios are calculated in month t+1.

Table 6 reports selected characteristics of the 25 size and IM portfolios. Panels A and B report the mean market capitalization and mean IM value in each portfolio. Panel C shows the mean number of stocks included in each portfolio. There are some notable observations in both Panels A and B. Reading across each row in Panel A, the average size tends to decrease. However, the difference is quite small except for the two largest size groups. Thus, the illiquidity premium (least liquid – most liquid) in the large size groups may be influenced by size. When reading down each column in Panel B, the mean IM value tends to decrease. This pattern is more pronounced in the two least liquid portfolios. These results could be due to the strong correlation between size and IM. Thus, some caution is needed when interpreting the illiquidity effect, especially among large size groups. Nonetheless, the results in Panels A and B show that we have been quite successful in controlling size across liquidity quintiles, and vice versa.

[18] We also explored the possibility of using portfolios triple sorted on size, IM and book-to-market. However, including the book-to-market dimension reduces the number of stocks in the portfolios to unacceptably low levels. Some portfolios have an average number of stocks less than 5. As a robustness check, we also consider portfolios double sorted on size and book-to-market, a point we shall return to later.

The number of stocks in Panel C is distributed unevenly across the 25 size and IM portfolios. The allocation to the top-left and bottom-right corners of the table is sparse. These two portfolios contain less than 10 stocks on average. This shows that most small (large) firms are less (more) liquid, which is to be expected. When used as the dependent variable, portfolios with a low number of stocks should be interpreted with caution.

[Insert Table 6 about here]

Table 4 also reports the mean and standard deviation of the monthly returns on the 25 size and IM portfolios. Panel D shows the average returns over the full sample period. The smallest size quintile generates the largest returns and there is a perfect monotonic decrease in returns within each IM quintile. Likewise, for the two smallest size quintiles, the average returns increase monotonically when moving from the most liquid quintile to the least liquid quintile. Except the two largest size groups, the difference in return between the least liquid quintile and the most liquid quintile is positive and significant at the 1% level. This result is consistent with the finding in Section 4.2 that the illiquidity premium only exists in small size firms. The standard deviations in Panel E are generally consistent with the patterns found in Panel D. Portfolios with a higher return exhibit a higher standard deviation. Special attention needs to be given to the bottom-right corner of the table as they contain relatively fewer stocks. The returns on these portfolios are the lowest and yet they exhibit high standard deviations.

5. Asset pricing tests

We run equation (5) on the 25 size and IM portfolio excess returns over the period from January 1982 to December 2006. The key aspects that we are looking at are (1) the relationship between IML and stock returns; and (2) the ability of the five-factor model in capturing the common variation in stock returns.

Table 7 reports the results of the five-factor model. Market beta (b) is significant and positive for all 25 portfolios. The loadings on SMB (s) are all positive and significant except for the largest size quintile. This indicates that SMB possesses strong explanatory power for small and medium-size firms. The loadings on HML (h) and MOM (m) are significant for 5 and 2 (out of 25) portfolios, respectively. However, there is no strong pattern of the factor loadings across the portfolios.

Recall that IML is the difference in returns between the least liquid portfolio and the most liquid portfolio. Given this formation technique, portfolios with stocks that are less (more) liquid should exhibit positive (negative) coefficients. Note that our focus is on the ability of IML to explain stock returns, and not necessarily the sign of the coefficients. The results show that the loadings on IML are related to liquidity. In general, the factor loadings increase monotonically when moving from the most liquid quintile to the least liquid quintile. They are generally positive in the least liquid portfolios and negative in the most liquid portfolios. This relationship is consistent with the manner in which IML is formed. It is also similar to the pattern for SMB with size and HML with book-to-market. There is also some evidence that small size groups exhibit higher IML loadings (in absolute terms) than big size groups. Moreover, the loadings on IML are significant for 7 (out of 25) portfolios. The significant relationship tends to be concentrated in low- and high-liquidity portfolios, which provides some evidence that IML helps capture the variation in stock returns related to liquidity that is not explained by the other factors. A joint test on the IML factor loadings indicates that the loadings on IML are not jointly equal to zero. Overall, the results in Table 7 indicate that IML is useful in pricing the test assets. The notable result from Table 7 is that 10 (out of 25) portfolios have significant regression intercepts. The null hypothesis that the 25 regression intercepts are jointly equal to zero is rejected, as both the J-statistic and GRS test are significant at the 1% level. Finally, the average adjusted R^2 is 0.54 for the 25 portfolios.

For the purpose of comparison, we run the Carhart four-factor model (equation (8)) on 25 size and IM portfolios. The results are displayed in Table 8. Compared to the results in Table 7, we see similar patterns in the factor loadings on Market, SMB, HML and MOM. The regression intercepts also exhibit very much the same pattern. However, 11 (out of 25) portfolios have significant regression intercepts and the average adjusted R^2 is 0.52 for the 25 portfolios. Overall, the results from Tables 7 and 8 suggest that liquidity explains a portion of the common variation in stock returns. However, the comparison of the regression intercepts and adjusted R^2s from Tables 7 and 8 reveals that adding a liquidity factor to the regression models results in only a marginal improvement in the model's ability to explain stock returns.

As a robustness check, we rerun equation (5) on the 25 size and book-to-market portfolios.[19] The intuition behind this test is that an asset pricing model should be able to explain the returns of portfolios that are created from the variables used to construct the risk factors. The results are displayed in Table 9. The regression intercepts are significant in 13

[19] The outcome of the individual regressions from the four-factor model on the 25 size and book-to-market portfolios are similar to those reported in Table 9. The results are available upon request.

out of 25 cases. Both the J-statistic and the GRS test again reject the null hypothesis and are significant at the 1% level. As expected, the slopes on SMB and HML are related to size and book-to-market, respectively. However, there is some evidence that HML has difficulty in explaining low book-to-market portfolios. In Table 9, we see that the momentum factor is not able to explain variation in stock returns that is related to size and book-to-market. There is also weak evidence that IML adds additional explanatory in explaining stock returns. These results strengthen the conclusions drawn from the earlier findings. Moreover, our results suggest that there remain omitted variables in pricing equity returns in Australia.

[Insert Tables 7, 8 & 9 about here]

6. Conclusion

Prior Australian studies on the role of liquidity in asset pricing have found mixed results. The current research re-examines the importance of liquidity as a factor in asset pricing in the context of the Fama-French (1993) framework over the period January 1982 to December 2006. We extend the existing Australian studies by (1) employing a different liquidity proxy and (2) using a longer and richer dataset. This is important for two reasons. First, the reliability of the inferences drawn from asset pricing studies increases as the length of the time series increases. Second, the new liquidity measure we propose only requires monthly data and thus is less intensive than a measure that requires daily data. Thus, our measure can be employed in asset pricing studies in smaller or developing markets where the ability to obtain daily share data over long periods is extremely limited.

The key findings of our research are as follows. First, we find that IM is related to liquidity and stock returns. The cross-sectional regressions demonstrate that IM is able to explain stock returns even after controlling for size, book-to-market and momentum. The results from the individual regressions provide some evidence that our liquidity factor helps explain the common variation in stock returns. This result supports the contention that liquidity has an important role in asset pricing. However, we find that augmenting asset pricing models with a liquidity factor only results in a marginal improvement in the model's explanatory power. This suggests that the asset pricing models examined are not able to fully explain the common variation in Australian equity returns.

Recently, Gharghori et al. (2007) find that augmenting the Fama-French model with additional factors such as a default, liquidity, leverage and momentum factor does not improve the model’s explanatory power. Our findings coincide with theirs. To this end, it remains an open question if there is a (are) variable(s) which can capture variation in stock returns that is left unexplained by the Fama-French factors in the Australian market. The search continues.

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Table 1 Summary statistics of the three sub-measures in constructing IM

This table reports descriptive statistics for the three standardised sub-measures used to construct IM. 1/PRICE is the reciprocal of stock price, ABSR is the absolute monthly stock return and BEEDLES is the thin trading measure proposed by Beedles et al. (1988). The three sub-measures are standardised so that they have zero cross-sectional sample mean and unit cross-sectional sample variance. The reported statistics are calculated cross-sectionally each month and then averaged over the sample period from January 1982 to December 2006.

Summary Statistics									
	Mean	Min	Lower Quartile	Median Quartile	Upper Quartile	Max	Standard Deviation	Skewness	Kurtosis
1/PRICE	0.00	-0.51	-0.45	-0.33	0.03	12.91	1.00	6.22	73.03
ABSR	0.00	-0.68	-0.66	-0.46	0.37	2.03	1.00	1.10	-0.03
BEEDLES	0.00	-0.72	-0.57	-0.28	0.23	13.21	1.00	5.62	75.12

Table 2 Correlation matrix of illiquidity proxies and trading characteristics

This table reports Spearman rank correlations for various liquidity proxies and trading characteristics. AMIHUD is the liquidity ratio from Amihud (2002). PS is the return reversal measure from Pastor and Stambaugh (2003). PBA is the proportional bid-ask spread. ZERO is the zero return measure from Lesmond et al. (1999). TO is the stock turnover rate. LIU is the turnover-adjusted zero daily volume measure from Liu (2006). IM is the proposed new illiquidity measure. The sign of PS and TO were flipped to make them represent illiquidity. PRICE is stock price at the end of each month. ABSR is the absolute monthly stock return. BEEDLES is the thin trading measure proposed by Beedles et al. (1988). All the variables are computed monthly. The correlations reported in the table are the time-series average of the monthly cross-sectional correlations over the period January 1991 to December 2006.

	AMIHUD	PS	PBA	ZERO	TO	LIU	IM	PRICE	ABSR	BEEDLES
AMIHUD	1									
PS	0.0263	1								
PBA	0.3175	0.2558	1							
ZERO	-0.0475	0.1207	0.3953	1						
TO	0.3928	0.2762	0.1999	0.2112	1					
LIU	0.4344	0.4122	0.5967	0.3788	0.6540	1				
IM	0.0969	0.1629	0.5635	0.2071	-0.0575	0.3219	1			
PRICE	-0.0654	-0.1079	-0.6831	-0.3806	0.1262	-0.2921	-0.6235	1		
ABSR	0.0568	-0.0131	0.2534	-0.0229	-0.2153	-0.0125	0.6822	-0.3113	1	
BEEDLES	0.1236	0.2618	0.3368	0.1858	0.2757	0.4718	0.5268	-0.1776	-0.0245	1

Table 3 Basic descriptive statistics and correlations

This table reports descriptive statistics and Spearman rank correlations for the variables used in the analysis. IM is the new illiquidity measure obtained from equation (1); SIZE is market capitalization measured in $millions; B/M is the book-to-market ratio; MOM is the cumulative return over the past 12 months with a one month lag, which was used to construct the Carhart (1997) momentum factor. The reported statistics are calculated cross-sectionally each month and then averaged over different sample periods. Panel A displays the results for our full sample period (January 1982 – December 2006). Panels B and C report the results for the first and second half sub-periods, respectively. The results related to B/M are separately calculated based on non-negative book-to-market stocks. We excluded stocks that did not trade in the current month when calculating IM.

	Summary Statistics									Spearman rank correlation			
	Mean	Min	Lower Quartile	Median Quartile	Upper Quartile	Max	Standard Deviation	Skew	Kurtosis	IM	SIZE	BM	MOM
Panel A: Full sample period													
IM	-0.25	-1.91	-1.46	-0.71	0.47	15.47	1.67	2.79	18.73	1			
SIZE	469.08	0.03	4.77	15.88	81.51	188097.64	5423.12	23.08	693.38	-0.5858	1		
BM	1.38	0.01	0.54	0.90	1.43	161.96	5.30	13.37	320.54	0.1355	-0.2425	1	
MOM	0.18	-1.89	-0.16	0.11	0.42	7.35	0.67	2.61	31.96	-0.1204	0.1778	0.0436	1
Panel B: January 1982 - December 1993													
IM	-0.28	-2.08	-1.56	-0.66	0.48	14.13	1.70	2.44	14.13	1			
SIZE	145.08	0.03	2.55	8.16	35.86	21639.09	885.80	14.32	281.14	-0.5630	1		
BM	1.71	0.01	0.67	1.08	1.69	255.99	7.93	13.69	342.76	0.1592	-0.2425	1	
MOM	0.20	-1.86	-0.16	0.13	0.44	7.95	0.69	2.85	33.79	-0.1184	0.1642	0.0567	1
Panel C: January 1994 - December 2006													
IM	-0.23	-1.75	-1.36	-0.75	0.47	16.70	1.64	3.12	22.97	1			
SIZE	768.15	0.04	6.81	23.01	123.66	341751.70	9611.42	31.16	1073.90	-0.6068	1		
BM	1.07	0.00	0.42	0.73	1.19	75.16	2.86	13.08	300.04	0.1135	-0.2424	1	
MOM	0.16	-1.91	-0.17	0.10	0.41	6.80	0.65	2.39	30.27	-0.1222	0.1904	0.0314	1

Table 4 Fama-MacBeth cross-sectional regressions

This table reports average Fama-MacBeth regression estimates using individual security data over our full sample period – January 1982 to December 2006. The dependent variable is the individual stock return at month t+1 and the explanatory variable set comprises various combinations of IM and firm characteristics that are known to affect stock returns at month t. IM is the new illiquidity measure obtained from equation (1); SIZE is market capitalization measured in $millions; B/M is the book-to-market ratio; MOM is the cumulative return over the past 12 months with a one month lag, which was used to construct the Carhart (1997) momentum factor. The coefficients are averaged across 300 trading months in the sample and the associated t-statistics are reported in parentheses below the coefficient estimates. The results related to B/M are obtained based on non-negative book-to-market stocks.

Regression	Constant	IM	SIZE	B/M	MOM
1	0.0230	0.0098			
	(6.29)**	(8.85)**			
2	0.1221		-0.0062		
	(8.04)**		(-8.06)**		
3	0.0163			0.0024	
	(4.87)**			(4.19)**	
4	0.0196				0.0014
	(6.30)**				(0.75)
5	0.0830	0.0075	-0.0036		
	(6.10)**	(7.95)**	(-5.32)**		
6	0.0212	0.0093		0.0018	
	(5.59)**	(8.02)**		(3.38)**	
7	0.0232	0.0100			0.0040
	(6.91)**	(9.15)**			(2.34)*
8	0.0809	0.0070	-0.0035	0.0011	
	(5.68)**	(6.98)**	(-4.95)**	(2.00)*	
9	0.0843	0.0072	-0.0037	0.0010	0.0043
	(6.13)**	(7.33)**	(-5.39)**	(1.99)*	(2.51)*

** and * denote significance at the 1% and 5% levels, respectively.

Table 5 Summary statistics for returns on the independent variable factor portfolios

This table reports summary statistics of monthly returns for the market excess return, SMB, HML, MOM, IML, IMLS and IMLB. SMB and HML are formed at the end of year t based on the intersection of independent size (50%:50%) and book-to-market (30%:40%:30%) sorts. Value-weighted portfolio returns are calculated monthly from January to December of year t+1. SMB is the difference between the average return of the three-small size portfolios and the average return of the three big size portfolios. HML is the difference between the average return of the two high book-to-market portfolios and the average return of the two low book-to-market portfolios. MOM is the difference between the equally-weighted return on the portfolio of firms with the highest 30 percent past returns and the equally-weighted return on the portfolio of firms with the lowest 30 percent past returns. The momentum portfolios are rebalanced on a monthly basis. IML is formed at the end of each month t based on the intersection of independent sorts on size (50%:50%) and IM (30%:40%:30%). Value-weighted portfolio returns are calculated in month t+1. The portfolios are rebalanced on a monthly basis. IML is the difference between the average return of the two least liquid portfolios and the average return of the two most liquid portfolios. IMLS (IMLB) is the difference between the return of the least liquid portfolio and the return of the most liquid portfolio in the small (big) size portfolios. The table shows the mean return (as a percentage), the standard deviation and the associated t-statistics for each factor. Panel A presents the summary statistics for the entire sample. Panel B presents the summary statistics after excluding the months of January and July. Panels C and D present the summary statistics for the first and second sub-periods, respectively.

	Factor portfolios						
	RM-RF	SMB	HML	MOM	IML	IMLS	IMLB
Panel A: January 1982 – December 2006							
Mean	0.39	3.21	0.65	0.53	1.98	4.09	-0.13
SD	0.05	0.07	0.04	0.05	0.05	0.08	0.06
t-stats	1.39	8.45**	2.68**	1.69	6.55**	8.47**	-0.40
Panel B: Full sample period: Excluding January and July							
Mean	0.21	2.60	0.66	0.57	1.43	3.13	-0.26
SD	0.05	0.06	0.04	0.06	0.05	0.08	0.06
t-stats	0.67	6.57**	2.40*	1.64	4.42**	6.42**	-0.74
Panel C: January 1982 - December 1993							
Mean	0.30	3.17	0.79	0.05	2.37	5.09	-0.35
SD	0.06	0.06	0.04	0.05	0.05	0.09	0.06
t-stats	0.57	6.66**	2.21*	0.10	5.49**	6.98**	-0.72
Panel D: January 1994 - December 2006							
Mean	0.48	3.25	0.51	0.97	1.63	3.17	0.08
SD	0.03	0.07	0.04	0.05	0.05	0.08	0.05
t-stats	1.94	5.57**	1.57	2.34*	3.85**	5.03**	0.19

** and * denote significance at the 1% and 5% levels, respectively.

Table 6 Characteristics of 25 Size and IM sorted portfolios

In each month t, stocks are ranked by their market capitalization and divided into quintiles. The same procedure is repeated for IM. 25 portfolios are formed from the intersection of independent size quintile and IM quintile sorts. We calculate the mean market capitalization, mean IM and the number of firms for each portfolio in each month. They are then averaged across the months from January 1982 to December 2006. The results are displayed in Panels A, B and C, respectively. Market capitalization is expressed in $millions. Top denotes the highest IM quintile portfolio (least liquid) and bottom denotes the lowest IM quintile portfolio (most liquid). In addition, value-weighted portfolio returns are calculated in month t+1. The portfolios are rebalanced on a monthly basis. The table shows the average return (Panel D) and standard deviation (Panel E) for each portfolio across the sample period. 5-1 is the difference in returns between the top and bottom portfolios.

Panel A: Market capitalization ($M)

	Bottom	2	3	4	Top
Small	2.65	2.71	2.66	2.59	2.28
2	7.61	7.54	7.33	7.18	6.86
3	20.54	19.75	19.16	18.58	17.86
4	74.37	71.21	67.15	63.24	60.81
Big	1757.87	1676.98	1197.81	1314.99	1621.52

Panel B: IM

	Bottom	2	3	4	Top
Small	-1.71	-1.31	-0.65	0.28	2.57
2	-1.70	-1.31	-0.66	0.24	2.04
3	-1.71	-1.33	-0.68	0.21	1.83
4	-1.72	-1.34	-0.7	0.18	1.75
Big	-1.73	-1.36	-0.75	0.16	1.62

Panel C: Number of firms

	Bottom	2	3	4	Top
Small	9	16	33	57	115
2	17	31	52	66	65
3	34	48	59	56	32
4	66	63	51	36	13
Big	104	71	34	13	4

Panel D: Mean monthly return (%)

	Bottom	2	3	4	Top	5-1
Small	3.69**	6.24**	9.00**	9.20**	13.28**	5.59**
2	3.26**	4.43**	5.11**	5.44**	6.91**	3.65**
3	2.49**	3.06**	3.75**	3.25**	5.04**	2.55**
4	2.08**	2.33**	2.84**	2.66**	2.16**	0.08
Big	1.60**	1.78**	1.46**	0.91**	-0.44	-2.05**

Panel E: Standard deviation (%)

	Bottom	2	3	4	Top
Small	11.11	15.55	15.67	12.59	13.77
2	8.38	9.04	10.88	9.91	1.30
3	6.17	7.46	8.51	7.07	10.25
4	3.97	4.82	6.34	6.74	9.42
Big	4.69	5.18	5.87	7.19	11.59

** and * denote significance at the 1% and 5% levels, respectively.

Table 7 Regression statistics from the five-factor model: January 1982 to December 2006 (25 Size and IM Portfolios)

$$RP_{jt} - RF_t = a_j + b_j[RM_t - RF_t] + s_j SMB_t + h_j HML_t + m_j MOM_t + i_j IML_t + e_{jt} \quad (5)$$

RP is the monthly return for one of the 25 size and IM portfolios; RF is the risk-free rate; RM is the monthly value-weighted market return; SMB, HML, MOM and IML are mimicking portfolios for size, book-to-market, momentum and liquidity, respectively. Top denotes the highest IM quintile portfolio (least liquid) and bottom denotes the lowest IM quintile portfolio (most liquid). The intercepts are reported as percentages. The regression is estimated using Generalised Method of Moments adjusted for Newey-West's heteroskedasticity-consistent covariance matrix.

			a						t-statistics		
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	1.21	2.64	3.50	3.40	7.03	Small	1.21	1.93	4.61**	5.13**	9.00**
2	1.11	1.74	1.03	0.48	1.89	2	1.38	2.22*	1.65	1.03	2.90**
3	0.37	0.66	0.16	0.09	1.27	3	0.83	1.12	0.41	0.27	2.02*
4	0.57	0.49	0.29	0.48	-0.84	4	2.41*	1.62	0.94	1.05	-1.45
Big	0.69	0.83	0.34	-0.71	-1.94	Big	5.65**	3.29**	1.27	-1.36	-2.05*
			b						t-statistics		
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.41	0.52	0.96	0.76	0.93	Small	2.06*	2.06*	4.30**	5.70**	6.85**
2	0.50	0.80	0.96	0.95	0.95	2	5.03**	4.51**	7.59**	9.39**	5.55**
3	0.66	0.71	1.01	0.85	0.79	3	4.56**	5.85**	12.28**	9.53**	6.57**
4	0.63	0.79	0.97	0.82	0.84	4	11.83**	13.92**	16.38**	9.54**	5.63**
Big	0.94	0.97	1.03	0.74	0.48	Big	15.34**	25.84**	19.33**	7.42**	2.48*
			s						t-statistics		
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.51	1.21	1.40	1.27	1.20	Small	2.74**	3.95**	3.89**	8.50**	8.04**
2	0.71	0.91	1.18	1.05	0.88	2	4.43**	5.39**	6.17**	6.63**	5.80**
3	0.51	0.60	0.78	0.64	0.55	3	4.28**	5.69**	8.38**	6.51**	5.21**
4	0.22	0.30	0.38	0.34	0.46	4	4.33**	4.70**	5.93**	4.28**	3.24**
Big	-0.01	-0.01	0.03	-0.10	-0.10	Big	-0.35	-0.28	0.40	-1.02	-0.52

Table 7 (continued)

	h						t-statistics				
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.16	0.11	0.47	0.61	0.52	Small	0.71	0.35	2.03*	1.74	2.26*
2	0.35	0.11	-0.18	0.39	0.22	2	1.79	0.60	-0.38	2.93**	1.04
3	0.21	-0.02	0.21	0.17	-0.07	3	1.11	-0.12	1.38	1.35	-0.47
4	0.10	0.16	0.20	0.00	0.17	4	1.72	2.39*	2.42*	-0.02	0.97
Big	0.01	-0.03	0.01	-0.06	0.01	Big	0.52	-0.37	0.14	-0.44	0.03
	m						t-statistics				
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.08	-0.32	-0.49	-0.24	-0.62	Small	0.38	-1.33	-1.48	-1.98	-4.48*
2	-0.06	-0.12	-0.06	-0.02	-0.19	2	-0.71	-0.96	-0.53	-0.28	-1.49
3	-0.11	-0.09	-0.08	-0.01	-0.11	3	-1.28	-0.99	-1.02	-0.24	-0.83
4	-0.07	-0.13	-0.02	0.13	-0.06	4	-1.30	-2.47*	-0.32	1.10	-0.44
Big	-0.04	0.01	0.00	0.14	0.10	Big	-1.07	0.19	0.06	1.39	0.50
	i						t-statistics				
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	-0.08	-0.55	-0.06	0.24	0.67	Small	-0.31	-1.10	-0.17	1.28	2.68**
2	-0.62	-0.63	-0.31	0.15	0.55	2	-2.41*	-1.80	-1.44	1.35	2.93**
3	-0.27	-0.22	-0.04	-0.01	0.56	3	-2.13*	-1.82	-0.46	-0.06	2.62**
4	-0.08	-0.08	0.06	0.00	0.21	4	-1.32	-1.36	0.87	0.03	1.20
Big	-0.05	-0.03	-0.03	0.47	0.45	Big	-2.02*	-0.84	-0.49	3.51**	1.72
	Adjusted R-squared										
	Bottom	2	3	4	Top						
Small	0.13	0.22	0.41	0.57	0.67	a = 0, J-Statistic = 301.94**; GRS = 16.70**					
2	0.25	0.44	0.66	0.75	0.67						
3	0.42	0.44	0.67	0.69	0.54						
4	0.65	0.70	0.74	0.54	0.37						
Big	0.93	0.85	0.74	0.45	0.10						

** and * denote significance at the 1% and 5% levels, respectively.

Table 8 **Regression statistics from the four-factor model: January 1982 to December 2006 (25 Size and IM Portfolios)**

$$RP_{jt} - RF_t = a_j + b_j[RM_t - RF_t] + s_j SMB_t + h_j HML_t + m_j MOM_t + e_{jt} \tag{8}$$

RP is the monthly return for one of the 25 size and IM portfolios; RF is the risk-free rate; RM is the monthly value-weighted market return; SMB, HML, MOM and IML are mimicking portfolios for size, book-to-market, momentum and liquidity, respectively. Top denotes the highest IM quintile portfolio (least liquid) and bottom denotes the lowest IM quintile portfolio (most liquid). The intercepts are reported as percentages. The regression is estimated using Generalised Method of Moments adjusted for Newey-West's heteroskedasticity-consistent covariance matrix.

			a						t-statistics		
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	1.18	2.45	3.48	3.48	7.26	Small	1.31	2.09*	5.00**	5.44**	8.15**
2	0.90	1.52	0.92	0.53	2.08	2	1.18	2.15*	1.60	1.20	2.85**
3	0.28	0.58	0.14	0.09	1.46	3	0.63	1.08	0.39	0.27	2.35*
4	0.55	0.46	0.31	0.48	-0.76	4	2.34*	1.59	1.03	1.17	-1.48
Big	0.67	0.81	0.33	-0.55	-1.79	Big	6.03**	3.57**	1.30	-1.04	-2.04*
			b						t-statistics		
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.40	0.46	0.95	0.79	1.01	Small	2.24*	2.22*	5.01**	6.44**	6.77**
2	0.43	0.73	0.93	0.97	1.01	2	4.09**	5.73**	7.47**	10.39**	5.38**
3	0.63	0.69	1.00	0.85	0.85	3	4.63**	6.71**	13.54**	10.75**	6.65**
4	0.63	0.78	0.98	0.82	0.86	4	13.00**	16.51**	17.50**	10.70**	5.91**
Big	0.93	0.97	1.03	0.79	0.53	Big	17.15**	29.67**	21.94**	8.63**	2.75**
			s						t-statistics		
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.47	0.95	1.37	1.39	1.52	Small	2.38*	4.99**	5.66**	9.20**	11.45**
2	0.42	0.61	1.03	1.12	1.14	2	3.52**	5.52**	7.47**	7.76**	9.35**
3	0.38	0.50	0.76	0.63	0.82	3	2.74**	5.32**	11.18**	7.91**	7.09**
4	0.18	0.26	0.41	0.34	0.56	4	3.83*	4.12**	7.99**	5.31**	5.47**
Big	-0.03	-0.03	0.01	0.13	0.12	Big	-1.86	-0.64	0.23	1.49	1.06

Table 8 (continued)

	h						t-statistics				
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.16	0.10	0.46	0.62	0.54	Small	0.76	0.33	2.19*	1.89	2.41*
2	0.33	0.09	-0.19	0.40	0.24	2	1.99*	0.60	-0.41	3.15**	1.11
3	0.20	-0.02	0.20	0.17	-0.05	3	1.15	-0.21	1.45	1.48	-0.34
4	0.10	0.16	0.21	0.00	0.18	4	1.69	2.59**	2.62**	-0.02	1.12
Big	0.01	-0.03	0.01	-0.04	0.02	Big	0.51	-0.41	0.13	-0.33	0.10

	m						t-statistics				
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
Small	0.08	-0.36	-0.50	-0.22	-0.57	Small	0.38	-1.37	-1.57	-1.89	-3.82*
2	-0.11	-0.17	-0.08	-0.01	-0.15	2	-1.33	-1.72	-0.72	-0.16	-1.04
3	-0.13	-0.11	-0.09	-0.02	-0.07	3	-1.43	-1.27	-1.22	-0.28	-0.47
4	-0.07	-0.14	-0.02	0.13	-0.04	4	-1.50	-2.90*	-0.28	1.17	-0.34
Big	-0.04	0.00	0.00	0.18	0.13	Big	-1.29	0.12	0.01	1.44	0.74

	Adjusted R-squared					
	Bottom	2	3	4	Top	
Small	0.12	0.20	0.41	0.57	0.63	a = 0, J-Statistic = 341.72**; GRS = 16.86**
2	0.16	0.36	0.64	0.75	0.63	
3	0.38	0.42	0.66	0.69	0.49	
4	0.64	0.70	0.74	0.54	0.36	
Big	0.92	0.85	0.74	0.38	0.08	

** and * denote significance at the 1% and 5% levels, respectively.

Table 9 **Regression statistics from the four-factor model: January 1982 to December 2006 (25 Size and BM Portfolios)**

$$RP_{jt} - RF_t = a_j + b_j[RM_t - RF_t] + s_j SMB_t + h_j HML_t + m_j MOM_t + i_j IML_t + e_{jt} \quad (5)$$

RP is the monthly return for one of the 25 size and IM portfolios; RF is the risk-free rate; RM is the monthly value-weighted market return; SMB, HML, MOM and IML are mimicking portfolios for size, book-to-market, momentum and liquidity, respectively. Top denotes the highest IM quintile portfolio (least liquid) and bottom denotes the lowest IM quintile portfolio (most liquid). The intercepts are reported as percentages. The regression is estimated using Generalised Method of Moments adjusted for Newey-West's heteroskedasticity-consistent covariance matrix.

	a						t-statistics				
	Low	2	3	4	High		Low	2	3	4	High
Small	1.94	1.89	2.53	1.09	2.76	Small	2.41*	2.69**	2.21*	1.64	5.74**
2	0.20	1.15	-0.12	0.62	0.34	2	0.29	1.61	-0.24	1.43	0.67
3	-0.52	0.13	0.26	0.90	0.72	3	-0.94	0.31	0.54	2.43*	1.89
4	0.26	0.17	0.58	1.21	0.92	4	0.56	0.63	2.45*	3.51**	2.41*
Big	0.62	0.58	0.62	0.98	0.98	Big	2.32*	3.49**	3.05**	3.61**	2.48*
	b						t-statistics				
	Low	2	3	4	High		Low	2	3	4	High
Small	0.80	0.89	1.17	0.75	1.02	Small	2.93**	4.90**	6.85**	3.60**	10.94**
2	1.05	0.93	0.86	0.72	1.04	2	6.90**	6.14**	6.77**	8.86**	10.91**
3	0.89	0.88	0.77	0.76	0.98	3	6.75**	12.13**	5.35**	15.46**	10.85**
4	0.93	0.81	0.79	0.62	0.89	4	12.26**	9.06**	17.35**	9.54**	6.49**
Big	0.95	0.94	0.95	0.95	0.79	Big	17.33**	15.07**	24.71**	16.15**	3.97**
	s						t-statistics				
	Low	2	3	4	High		Low	2	3	4	High
Small	1.23	1.11	1.54	1.21	1.08	Small	7.43**	7.64**	6.05**	7.46**	9.82**
2	0.99	1.24	0.93	0.77	1.05	2	6.38**	5.43**	8.21**	8.21**	7.01**
3	0.86	0.66	0.66	0.44	0.48	3	6.73**	6.35**	5.61**	5.88**	4.34**
4	0.26	0.30	0.25	0.16	0.19	4	3.56**	4.99**	5.24**	2.84**	1.88
Big	-0.08	0.01	-0.03	-0.07	0.00	Big	-2.10*	0.17	-0.77	-1.23	-0.05

Table 9 (continued)

	h						t-statistics				
	Low	2	3	4	High		Low	2	3	4	High
Small	-0.01	-0.21	0.42	0.60	0.72	Small	-0.04	-0.99	1.83	1.94	3.32**
2	-0.33	-0.08	0.25	0.36	0.71	2	-1.03	-0.29	1.72	3.75**	4.61**
3	-0.51	0.13	0.23	0.22	0.45	3	-1.65	1.03	1.18	2.41*	2.36*
4	-0.02	0.22	0.07	-0.08	0.41	4	-0.16	3.03**	1.22	-0.52	2.34*
Big	-0.21	-0.06	0.03	0.20	0.54	Big	-2.71**	-1.32	0.56	2.19*	3.32**
	m						t-statistics				
	Low	2	3	4	High		Low	2	3	4	High
Small	-0.12	0.21	0.06	0.14	-0.23	Small	-0.65	1.65	0.30	0.99	-1.70
2	-0.28	-0.07	-0.03	-0.01	-0.05	2	-1.58	-0.60	-0.36	-0.16	-0.50
3	0.08	0.06	-0.09	-0.04	-0.01	3	0.85	0.76	-0.83	-0.50	-0.20
4	-0.06	-0.04	-0.03	-0.06	-0.04	4	-0.62	-0.57	-0.53	-1.05	-0.46
Big	-0.05	-0.06	0.00	-0.06	-0.06	Big	-0.98	-1.83	0.11	-1.30	-0.50
	i						t-statistics				
	Low	2	3	4	High		Low	2	3	4	High
Small	0.40	0.21	-0.63	0.19	0.39	Small	2.05*	1.33	-1.13	0.84	1.53
2	0.30	-0.09	0.14	0.00	-0.09	2	1.88	-0.41	1.19	0.01	-0.72
3	-0.12	-0.04	-0.03	-0.12	0.01	3	-0.87	-0.49	-0.24	-1.43	0.08
4	0.09	0.04	-0.08	-0.05	0.10	4	1.23	0.50	-1.25	-0.83	0.90
Big	0.03	-0.07	0.04	0.04	0.00	Big	0.67	-1.77	0.72	0.69	-0.04
	Adjusted R-squared										
	Low	2	3	4	High						
Small	0.59	0.60	0.51	0.54	0.65	a = 0, J-Statistic =679.51**; GRS = 10.41**					
2	0.65	0.56	0.68	0.60	0.72						
3	0.66	0.66	0.42	0.57	0.58						
4	0.63	0.68	0.70	0.50	0.51						
Big	0.83	0.89	0.82	0.73	0.43						

** and * denote significance at the 1% and 5% levels, respectively.

Appendix

This appendix outlines the six illiquidity measures used as benchmarks for comparison in this paper.

1. Amihud Illiquidity ratio

The monthly illiquidity ratio is obtained from the following equation:

$$Illiquid_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} | r_{i,d,t} | / v_{i,d,t} \qquad \text{(A1)}$$

where $r_{i,d,t}$ is the absolute return for stock i on day d in month t, and $v_{i,d,t}$ is the trading volume in millions of dollars for stock i on day d in month t and D is the number of daily observations for stock i in month t.

2. The return reversal measure

The return reversal measure, developed by Pastor and Stambaugh (2003), captures the price changes associated with order flow. The monthly return-reversal measure for security i is obtained by running the following OLS regression:

$$r^{e}_{i,t+1} = \gamma_0 + \gamma_1 r_{i,t} + \lambda[sign(r^{e}_{i,t}) \times vol_{i,t}] + \varepsilon_{i,t} \qquad \text{(A2)}$$

where $r^{e}_{i,t+1}$ is the excess return with respect to the value-weighted market index return for firm i on day t+1, $r_{i,t}$ is the return for firm i on day t, $sign(r^{e}_{i,t})$ is the sign of the excess return with respect to the value-weighted market index return for firm i on day t, and $vol_{i,t}$ is the trading volume in millions of dollars for firm i on day t. The coefficient λ measures the expected return reversal for a given trading volume.

3. Proportional spread

The proportional bid-ask spread for stock i in month t is given by:

$$pspread_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} (p^{A}_{i,d,t} - p^{B}_{i,d,t}) / (0.5 p^{A}_{i,d,t} + 0.5 p^{B}_{i,d,t}) \qquad \text{(A3)}$$

where $p^{A}_{i,t}$ ($p^{B}_{i,t}$) is the daily end ask (bid) prices for stock i in month t.

4. Zero return measure

The monthly proportion of zero returns is calculated as:

$$zero_{i,t} = zeroreturn_{i,t} / tradingday_{i,t} \tag{A4}$$

where $zeroreturn_{i,t}$ is the number of zero return days for stock i in month t, and $tradingday_{i,t}$ is the number of trading days for stock i in month t.

5. Stock turnover

Stock turnover is the ratio of the number of shares traded to the number of shares outstanding:

$$turnover_{i,t} = VOL_{i,t} / share_{i,t} \tag{A5}$$

where $VOL_{i,t}$ is the total trading volume for stock i in month t and $share_{i,t}$ is the number of shares outstanding for stock i in month t.

6. Turnover-adjusted number of zero daily volumes

Liu (2006) proposes a new liquidity measure that aims to capture multiple dimensions of liquidity and places a particular focus on trading speed. The liquidity measure is defined as:

$$LM_x = [NoZV + \frac{1/(xmonthturnover)}{Deflator}] \times \frac{21x}{NoTD} \tag{A6}$$

where *NoZV* and x-month turnover are the number of zero daily volumes and share turnover over the prior x months. *NoTD* is the total number of trading days in the market over the prior x months, and the deflator[20] is set to 480,000 as suggested in Liu (2006). We focus on the monthly LM (i.e. x = 1).

[20] The reciprocal of turnover produces a wide range of numbers that can be very large or very small, depending on the magnitude of the monthly turnover rate. The deflator is used to ensure that $0 < [(1/xmonthturnover)/deflator]$ < 1, so stocks that have the same number of zero daily volumes (*NoZV*) can be further differentiated.