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A liquidity-augmented capital asset pricing model ☆

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Abstract

Using a new measure of liquidity, this paper documents a significant liquidity premium robust to the CAPM and the Fama–French three-factor model and shows that liquidity is an important source of priced risk. A two-factor (market and liquidity) model well explains the cross-section of stock returns, describing the liquidity premium, subsuming documented anomalies associated with size, long-term contrarian investment, and fundamental (cashflow, earnings, and dividend) to price ratios. In particular, the two-factor model accounts for the book-to-market effect, which the Fama–French three-factor model fails to explain.

JEL classification: G12; G14

Keywords: Trading speed; Liquidity premium; Liquidity factor

1. Introduction

Liquidity is generally described as the ability to trade large quantities quickly at low cost with little price impact. This description highlights four dimensions to liquidity, namely, trading quantity, trading speed, trading cost, and price impact. For at least the last ten years, researchers have examined the importance of liquidity in explaining the cross-section

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of asset returns, and empirical studies have employed several liquidity measures. Existing measures typically focus on one dimension of liquidity. For example, the bid-ask spread measure in Amihud and Mendelson (1986) relates to the trading cost dimension, the turnover measure of Datar et al. (1998) captures the trading quantity dimension, and the measures in Amihud (2002) and Pastor and Stambaugh (2003) employ the concept of price impact to capture the price reaction to trading volume. However, there is little published research devoted to capturing the trading speed dimension of liquidity. Also, since liquidity is multidimensional, existing measures inevitably demonstrate a limited ability to capture liquidity risk fully and they may be inaccurate even in the dimension they aim to capture.[1] Although the evidence shows that liquidity risk plays an important role in explaining asset returns, few studies incorporate a liquidity risk factor into an asset pricing model, and those that do observe limited success in explaining cross-sectional variation in asset returns.[2] Even less is known about whether liquidity risk can explain the various anomalies that the asset pricing literature documents. This study contributes to the literature by addressing these three issues. That is, I seek to fill the gap with respect to the liquidity measure, the relation between liquidity risk and asset pricing, and the relation between liquidity risk and anomalies.

In the first part of this study, I propose a new liquidity measure for individual stocks, which I define as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. This measure captures multiple dimensions of liquidity such as trading speed, trading quantity, and trading cost, with particular emphasis on trading speed, that is, the continuity of trading and the potential delay or difficulty in executing an order. Consistent with the multidimensionality of liquidity, the new liquidity measure is highly correlated with the commonly used bid-ask spread, turnover, and return-to-volume measures. As I show in Section 2, however, the new measure is materially different from existing measures. I find that the stocks that the new liquidity measure identifies as less liquid tend to be small, value, low-turnover, high bid-ask spread, and high return-to-volume stocks, consistent with intuition. The new liquidity measure can predict stock returns one or more years ahead. The least liquid decile stocks significantly outperform the most liquid decile stocks by, on average, 0.682% per month over a 12-month holding period. This predictability is not due to a specific subperiod or to a January effect per se although the liquidity premium in January is about 2% higher than in non-January months. Also, the liquidity premium is robust to various controls for firm characteristics known to be associated with stock returns such as size, book-to-market, turnover, low price, and past intermediate-horizon returns. To address the neglected firm effect of Arbel and Strebel (1982), I also examine the liquidity effect based on NYSE stocks only. Within

[1] Pastor and Stambaugh (2003) describe any liquidity measure as "somewhat arbitrary." Their own measure is based on one from a class of 24 regression specifications. They argue, however, that while their liquidity measure for individual stocks is imprecise, their market-wide liquidity measure becomes more precise as the sample size becomes large. Similarly, Amihud (2002) states that a single measure cannot capture liquidity and thus he describes his measure as a "rough" measure of price impact. Based on the finding of Lee (1993) that many large trades occur outside the spread and many small trades occur within the spread, Brennan and Subrahmanyam (1996) point out that the quoted bid-ask spread is a noisy measure of liquidity. Lee and Swaminathan (2000) present evidence that high-turnover stocks behave more like small stocks than low-turnover stocks, questioning the common interpretation of turnover as a liquidity proxy.

[2] Pastor and Stambaugh (2003) lead the way here by incorporating a liquidity factor into the Fama–French three-factor model. They show that their liquidity risk factor explains half of the profits to a momentum strategy over the period 1966–1999.

NYSE stocks, not only does the return difference between the least liquid decile and the most liquid decile remain significant, but the return difference between the second-least liquid decile and the most liquid decile is also significant. This indicates that the liquidity premium remains significant after excluding the decile of stocks with the largest number of days without trades, which is likely to consist of those stocks that investors are unaware of or that they simply find uninteresting. Moreover, neither the capital asset pricing model (CAPM) nor the Fama–French three-factor model can account for the liquidity premium.

The pronounced premium associated with the new liquidity measure raises two immediate questions: Why is there a liquidity premium? What causes a stock to be less liquid? While the importance of liquidity has been a subject of research for over a decade, liquidity risk is newer territory. Nevertheless, recent developments shed promising light on the role that liquidity risk plays in explaining asset prices. For instance, Lustig (2001) argues that solvency constraints give rise to liquidity risk. In Lustig's model, investors demand a higher return on stocks to compensate for business cycle-related liquidity risk, that is, low stock returns in recessions. In addition, Lustig (2001) shows that an equity's sensitivity to liquidity raises its equilibrium expected return. Focusing on the corporate demand for liquidity, Holmstrom and Tirole (2001) develop a liquidity-based asset pricing model and show that a security's expected return is related to its sensitivity to aggregate liquidity. More recently, and similar to the solvency constraints argument of Lustig (2001), Pastor and Stambaugh (2003) argue that any investor who employs some form of leverage and faces a solvency constraint will require higher expected returns for holding assets that are difficult to sell when aggregate liquidity is low. They find that stocks with high sensitivity to aggregate liquidity generate higher returns than low-sensitivity stocks, and conclude that market-wide liquidity is an important state variable for asset pricing. The new liquidity measure that I introduce in this paper is designed in particular to emphasize order execution difficulty.

Assuming the average investor faces solvency constraints, we can consider the factors that affect a security's liquidity, even if, as Pastor and Stambaugh (2003) observe, the complete economic theory has yet to be formally modeled. First, liquidity becomes a relevant issue when the economy is in or is expected to be in a recessionary state. From the viewpoint of asset allocation, risk-averse investors prefer to invest in less risky, more liquid assets if they anticipate a recession. This is consistent with Hicks' (1967) "liquidity preference" notion, according to which investors hold financial assets not only for their returns but also to facilitate adjustments to changes in economic conditions, with Chordia et al. (2005), who show that stock market liquidity is associated with monetary policy and that fluctuations in liquidity are pervasive across stock and bond markets, and with Eisfeldt (2002), who models endogenous fluctuations in liquidity along with economic fundamentals such as productivity and investment. Moreover, it may be difficult for corporations to raise funds in the capital markets when the economy is performing poorly, in which case companies have an incentive to hoard liquidity (see, e.g., Holmstrom and Tirole, 2001). Second, asymmetric information can create illiquidity. If there are insider traders who possess private information in the market and (uninformed) investors become aware of this, then the uninformed investors will choose not to trade, which in turn will restrict liquidity. At the extreme, the market can collapse. Therefore, the private information premium that Easley et al. (2004) study can be related to or captured by the liquidity premium. Third, firms themselves can cause (il)liquidity. Everything else equal, no investor is interested in holding the shares of a company that has a high probability of default or has a poor management team. Although the relation between default and liquidity is not the focus of this study, I conjecture that liquidity risk can, to some extent, capture any default premium. Likewise, distressed firms are unattractive to investors and thus are less liquid. Indeed, I find that small and high book-to-market stocks are less liquid. It seems plausible, therefore, that a liquidity factor captures distress risk more directly than the size and book-to-market proxies used in the Fama–French three-factor model.

The evidence that liquidity is an important state variable for asset pricing (Pastor and Stambaugh, 2003) and the limited power of the Fama–French three-factor model to describe the cross-section of asset returns (see, for example, Daniel and Titman, 1997) motivate me in the second part of this study to develop a liquidity-augmented asset pricing model. Specifically, I develop a two-factor augmented CAPM that comprises both market and liquidity factors. This is in line with O'Hara (2003), who argues that transactions costs of liquidity and risks of price discovery need to be incorporated into asset pricing models. I construct the liquidity factor as the profits of the mimicking portfolio that buys \$1 of the low-liquidity portfolio and sells \$1 of the high-liquidity portfolio. I find that the mimicking liquidity factor is highly negatively correlated with the market, reflecting its nature as a state variable—when the economy performs badly, causing liquidity to be low, investors require a high liquidity premium to compensate them for bearing high liquidity risk. To further examine how well the mimicking portfolio represents the underlying liquidity risk factor, I construct a market-wide liquidity measure and estimate the innovations in market liquidity based on the new liquidity measure I propose in this study.[3] The aggregate liquidity measure seems to describe market liquidity conditions, and the obvious low-liquidity periods are those following significant economic and financial events such as the 1973 oil embargo, the 1987 crash, and the burst of the hi-tech bubble. The new aggregate liquidity measure is highly correlated with other market-wide liquidity measures such as price impact-based and turnover-based market liquidity, and the mimicking liquidity factor is significantly correlated with innovations in market liquidity, that is, the underlying liquidity factor. Both innovation-based and mimicking factor-based historical liquidity betas predict future returns as more liquidity-sensitive stocks earn higher expected returns. A significant generalized method of moments (GMM) estimate of the liquidity risk premium further confirms the notion that liquidity is an important source of priced risk for asset pricing.

The third part of this paper explores the role that liquidity risk plays in explaining the various pricing anomalies documented in the finance literature, a question that Pastor and Stambaugh (2003) suggest is a direction for future research. The two-factor model I develop is successful in explaining the documented anomalies. Specifically, it describes the liquidity premium that both the CAPM and the Fama–French three-factor model fail to capture and subsumes the effects due to size, book-to-market, cash-flow-to-price, earnings-to-price, dividend yield, and long-term contrarian investment. In contrast, the CAPM performs poorly against these market anomalies and the Fama–French three-factor model has only limited power in explaining some of these anomalies. In particular, besides failing to capture the liquidity premium, the Fama–French three-factor model cannot explain the book-to-market effect in spite of the fact that it includes a book-to-market factor. The state nature of liquidity and the conjecture that liquidity risk captures distress risk more

[3]In Section 5, I explain why I do not use the innovations in market liquidity directly as the liquidity factor.

directly than the size and book-to-market factors explain the favorable performance of the two-factor model. The success of this augmented CAPM provides support for the risk–return paradigm.

The remainder of the paper continues as follows. The next section discusses the construction of the liquidity measure. Section 3 describes the data. Section 4 presents the empirical evidence on the liquidity premium. Section 5 focuses on the construction and verification of the liquidity factor and tests the performance of the two-factor model. The final section concludes.

2. The liquidity measure

I define the liquidity measure of a security, LMx, as the standardized turnover-adjusted number of zero daily trading volumes over the prior x months ($x = 1, 6, 12$), that is,

$$LMx = \left[\textit{Number of zero daily volumes in prior x months} + \frac{1/(\textit{x-month turnover})}{\textit{Deflator}} \right] \times \frac{21x}{NoTD}, \tag{1}$$

where *x-month turnover* is turnover over the prior x months, calculated as the sum of daily turnover over the prior x months, daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day, $NoTD$ is the total number of trading days in the market over the prior x months, and *Deflator* is chosen such that

$$0 < \frac{1/(\textit{x-month turnover})}{\textit{Deflator}} < 1$$

for all sample stocks.[4]

Given the turnover adjustment (the second term in the square brackets of Eq. (1)), two stocks with the same integer number of zero daily trading volumes can be distinguished: the one with the larger turnover is more liquid. Thus, the turnover adjustment acts as a tie-breaker when sorting stocks based on the number of zero daily trading volumes over the prior x months. Because the number of trading days in a month can vary from 15 to 23, multiplication by the factor $21x/NoTD$ standardizes the number of trading days in a month to 21, which makes the liquidity measure comparable over time. For instance, $LM1$ can be interpreted as the turnover-adjusted number of zero daily trading volumes over the prior 21 trading days (approximately the average number of trading days in a month), and $LM12$ as the turnover-adjusted number of zero daily trading volumes over the prior 252 trading days (approximately the average number of trading days in a year). I construct the liquidity measure (LMx) at the end of each month for each individual stock based on daily data. This construction requires daily trading volume data over the prior x months, which slightly reduces the sample size. For example, the requirement for 12-month daily trading volume data—the longest period required—reduces the number of NYSE/AMEX sample stocks by, on average, 6.615% over the 1963–2003 period compared with the requirement for 12-month return data only. The lack of trading volume data for these stocks may be due to the fact that they are less frequently traded. Hence, excluding them might result in a

[4]I use a deflator of 11,000 in constructing $LM6$ and $LM12$, and a deflator of 480,000 for $LM1$.

downward bias in tests for a liquidity premium. Note that for individual NYSE/AMEX (NASDAQ) ordinary common stocks, the maximum $LM12$ is 249 (251), and using a shorter period such as one month or six months to construct the liquidity measure fails to distinguish some illiquid stocks whose daily trading volumes over the prior one or six months are all equal to zero. Therefore, I mainly adopt $LM12$ as the liquidity measure in the empirical analysis.

The new liquidity measure given by Eq. (1) captures multiple dimensions of liquidity, placing particular emphasis on trading speed, which existing research largely ignores. First, the number of zero daily trading volumes over the prior x months captures the continuity of trading and the potential delay or difficulty in executing an order. In other words, the absence of trade in a security indicates its degree of illiquidity: the more frequent the absence of trade, the less liquid the security. In extreme cases of zero trading volumes, the measure captures “lock-in risk,” the danger that assets cannot be sold.[5] This concept of lock-in risk shares some similarity with the ‘liquidity risk’ of Gallmeyer et al. (2004), which refers to uncertainty about the terms-of-trade investors face. Thus, the liquidity measure in this study captures the basic intuition that investors are afraid to hold stocks in which they are likely to face lock-in risk. Accordingly, I expect that investors require higher expected returns for holding stocks with high probabilities of lock-in. Indeed, the empirical evidence below shows that lock-in risk is the most pronounced generator of the liquidity premium. Of course, there may be cases in which some investors do not have solvency constraints and thus they keep their holdings for a long period. If this is the case, the new liquidity measure will underestimate the liquidity premium. However, Pereira and Zhang (2004) find that uncertainty about the investment horizon substantially increases the liquidity premium, indicating that liquidity is also relevant to long-term investors.

Second, the turnover adjustment enables the new liquidity measure to capture, to a certain extent, the dimension of trading quantity. From the construction of the liquidity measure, sorting stocks into LMx-based portfolios is equivalent to a dependent double sort, with the first sort on the pure number of zero daily trading volumes over the prior x months (the speed dimension) and the second sort on turnover (the quantity dimension). Specifically, conditional on the number of zero trading volume days, stocks with high (low) turnover are more (less) liquid. Empirically, on average over 50% (30%) of NYSE/AMEX (NASDAQ) stocks trade every day throughout the prior 12 months. Hence, the stocks that the new liquidity measure identifies as most liquid are those traded every day with large turnovers over the prior x months. However, the pure number of zero daily trading volumes principally determines the least liquid stocks that we are particularly interested in. In sum, LMx uses the pure number of zero daily trading volumes over the prior x months to identify the least liquid stocks, but it relies on turnover to distinguish the most liquid among frequently traded stocks as classified by the pure number of zero trading volumes.

Third, the new liquidity measure reflects the trading cost dimension of liquidity: the more liquid the stock, the less costly it is for investors to trade. Lesmond et al. (1999) model transaction costs based on the frequency of zero-return days, which could be due to the absence of trades. In their model, zero returns or no trades occur if transaction costs

[5]Of course, investors who want to trade might receive a quote. However, the quote they receive may be unfavorable, such that they would realize a considerable loss if they traded on the quote, in which case they choose not to trade. This choice of no trading is different from the disposition effect because the liquidity measure proposed in this study can predict high future returns, as Section 4 documents.

are high and the information value to trading does not exceed the transaction cost threshold. Their empirical evidence indicates that the number of zero returns is a good proxy for transaction costs. Given the close link between zero returns and no trades, the new liquidity measure can capture a great extent of the trading cost dimension of liquidity.

The empirical evidence shows that the new liquidity measure is highly correlated with the commonly used bid-ask spread and turnover measures, confirming that the new liquidity measure captures the multidimensional features of liquidity. It is also highly correlated with the return-to-volume measure of Amihud (2002), which Amihud proposes to capture the price-impact dimension of liquidity. The new measure is materially different from these existing measures, however. First, consider the liquidity measure of Amihud and Mendelson (1986), which is the average of the beginning- and end-of-year relative spreads. Suppose there are two stocks A and B and they have the same average relative spread, but over the prior year trading activity has taken place on 200 days in the case of A and on 10 days in the case of B. Clearly, we would describe B as less liquid than A; this is the result that obtains using the liquidity measure of this study. Second, the analysis below sorts stocks into liquidity deciles. An earlier analysis that does not adopt the turnover adjustment and that uses the pure number of zero daily trading volumes over the prior 12 months gave qualitatively similar results to those reported below. By contrast, the return predictability of the turnover measure, which is defined as the average daily turnover over the prior 12 months, is weak, and it fails to predict a significant return difference between low-turnover and high-turnover stocks over the period January 1963 to December 1983 (see Panel A of Table A.1 in the appendix). Because the pure number of zero daily trading volumes predicts returns better than the turnover measure, the speed dimension of liquidity predicts returns better than the quantity dimension. This is consistent with it being inappropriate to regard a large amount of trading, e.g., from a buy-initiated order, as a signal of liquidity if the investor cannot subsequently sell some or all of his shares. Third, given that the liquidity premium is largely driven by infrequently traded stocks (high lock-in risk), the new liquidity measure is distinct from the liquidity measures in Amihud (2002) and Pastor and Stambaugh (2003), since these latter measures are constructed by partially excluding the effect of the absence of trading on liquidity. In particular, the liquidity measure of Amihud (2002) is defined as the ratio of the daily absolute return to daily dollar trading volume averaged over one year. Clearly, if a stock's trading volume is zero on a particular trading day, its return-to-volume ratio cannot be calculated. Moreover, the three factors of Fama–French can empirically explain the return-to-volume effect (see Panel C of Table 8), and the return-to-volume measure has no predictive power for security returns over the recent 20-year period January 1984 to December 2003 (see Table A.1, Panel B in the appendix). The liquidity measure of Pastor and Stambaugh (2003) is estimated by an ordinary least squares (OLS) coefficient on signed trading volume, where the estimate is based on daily data over a one-month interval with a minimum of 16 observations. If a stock does not trade or the number of days on which trading takes place is less than 16 throughout an entire month, its liquidity measure cannot be estimated. This might be one reason why their liquidity measures are less precise at the individual stock level. Fourth, the new liquidity measure is also distinct from the measure of liquidity employed by Bekaert et al. (2003), which is based on the proportion of zero daily firm returns. Because a zero-return observation could be due to the absence of trades, the proportion of zero returns can be a useful liquidity proxy in markets in which volume data are unavailable, as in many emerging markets. However, using the proportion of zero daily firm returns as a liquidity measure is problematic if return data are based on price quotes. Based on Datastream daily returns, as used by Bekaert et al. (2003), I find that the Bekaert et al. (2003) measure indicates high liquidity for October 1987, when the market was in fact highly illiquid. This result obtains because Datastream returns are calculated based on closing midprice quotes rather than transaction prices.

3. Data and research design

The sample comprises all NYSE/AMEX/NASDAQ ordinary common stocks over the period January 1960 to December 2003.[6] Because trading volumes for NASDAQ stocks are inflated relative to NYSE/AMEX stocks due to interdealer trades, I examine the liquidity effect separately for NYSE/AMEX stocks and NASDAQ stocks, with a comprehensive examination of liquidity based on NYSE/AMEX stocks. Daily trading volume, number of shares outstanding, bid and ask prices, monthly return, market value (MV), and annual accounting data for calculating the book-to-market (B/M), cashflow-to-price (C/P), and earnings-to-price (E/P) ratios come from the CRSP/COMPUSTAT merged (CCM) database. The construction of B/M, C/P, and E/P follows the methods that Kenneth French's website shows.[7] I assume a minimum five-month gap between the fiscal year-end date and the actual report release date when using book equity, cashflow, and earnings to calculate B/M, C/P, and E/P. Following Fama and French (1988), I also compute dividend yields (D/P) for individual stocks at the beginning of each month based on the total dividend paid over the prior 12 months. In tests that involve B/M, the test sample excludes financial and negative-B/M stocks. Otherwise, I impose no such restrictions. I download the monthly values of the three Fama–French factors—market (MKT), size (SMB), and book-to-market (HML)—from Kenneth French's website.

To demonstrate the relative usefulness of the new liquidity measure described in Section 2, I also calculate and examine turnover, the return-to-volume ratio, and the bid-ask spread, as each of these captures a different dimension of liquidity. I define the turnover measure, $TO12$, as the average daily turnover over the prior 12 months; $TO12$ is similar to measures used in Datar et al. (1998) and Lee and Swaminathan (2000). I define the return-to-volume measure, $RtoV12$, as that of Amihud (2002), which is the ratio of the absolute return on a particular day to the dollar trading volume on that day averaged over the prior 12 months. The calculation of $RtoV12$ excludes zero daily trading volumes. I define the bid-ask spread measure, $BA12$, as the average daily relative bid-ask spread over the prior 12 months, where daily relative spread is the dollar spread divided by the ask price. Because of data limitations on bid and ask prices, I calculate $BA12$ from available bid and ask prices over the prior 12 months. This measure is similar to the one used by Amihud and Mendelson (1986), and it is only available for NASDAQ stocks over the period 1984 to 2003 in this study.

[6] I identify ordinary common stocks using CRSP share codes 10 and 11. For tests of long-term overreaction that involve a four-year ranking period, the sample period is January 1960 to December 2003. For the majority of tests, which require one year of information prior to portfolio formation, the sample period is January 1963 to December 2003. The sample period is limited by the use of daily CRSP data, which are available from July 1962 for NYSE/AMEX stocks. NASDAQ stocks are included from January 1983 onwards since their daily data on trading volume and bid and ask prices are available only from November 1982.

[7] Kenneth French's website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

Table 1 presents summary statistics for the main variables in this study. For NYSE/AMEX stocks over the period 1963 to 2003, Table 1, Panel A shows that, on average, there are 10.4 zero trading volume days (half a month) over the prior 12 months (252 trading days). On average, for 105 stocks, the number of zero daily trading volumes exceeds 63 throughout the prior 252 trading days, and for 168 stocks, the number of zero trading volume days lies between 21 and 63. Thus, the distribution of the new liquidity measure is well-dispersed. As expected, the new liquidity measure is highly negatively correlated with the turnover measure at −0.74, indicating that the new liquidity measure well captures the trading quantity feature of liquidity. The new liquidity measure is also negatively correlated with size at −0.51, implying that small firms are less liquid and size could be a reasonable proxy for liquidity. The correlation between $LM12$ and B/M is positive (around 0.24), consistent with expectations. In addition, the new liquidity measure is highly correlated with the return-to-volume measure ($RtoV12$) at 0.66, revealing that the new liquidity measure captures, to some extent, the price impact dimension of liquidity. However, $RtoV12$ is nearly perfectly negatively correlated with MV at −0.944. As a result, it is not surprising that the Fama–French three-factor model can subsume the return-to-volume effect (see Panel C of Table 8), and $RtoV12$ fails to predict returns at all over the recent two decades (see Table A.1, Panel B in the appendix), consistent with the disappearance of the size effect.

Table 1, Panel B shows similar results based on NASDAQ stocks over the period 1983 to 2003. As expected, NASDAQ stocks are, on average, smaller and less liquid than NYSE/AMEX stocks. The new liquidity measure is highly correlated with the relative bid-ask spread at 0.69, indicating the ability of the new liquidity measure to capture the liquidity dimension of trading costs. This is also consistent with Easley et al. (1996), who find that infrequently traded stocks tend to have larger spreads than actively traded stocks. The correlation between size (MV) and the bid-ask spread ($BA12$) is highly negative at −0.85, implying that trading in small stocks can be very costly. Because both $RtoV12$ and $BA12$ are highly negatively correlated with size, the correlation between $RtoV12$ and $BA12$ is high at 0.94. The turnover measure ($TO12$) and spread ($BA12$) are negatively correlated at −0.50, which is lower (in absolute terms) than the correlations of the new liquidity measure with $TO12$ and $BA12$. This reflects the fact that the two measures, turnover and spread, capture different dimensions of liquidity. This also suggests that the new liquidity measure combines some of the unique information contained in the turnover and bid-ask spread measures, consistent with the intent of the new measure.

The basic research design involves sorting stocks into portfolios S through B based on a variable of interest. Portfolio B can be interpreted as a buy-side portfolio representing the highest $LM12$, or B/M, and the lowest MV portfolios, and portfolio S can be regarded as a short-side portfolio representing the lowest $LM12$, or B/M, and the highest MV portfolios. To increase power and to moderate the sensitivity of portfolio returns to the initiation month, portfolios involve overlapping ranking and testing periods (results are similar using nonoverlapping holding periods). Specifically, at the beginning of each month, stocks are sorted into portfolios and held for n ($n = 1, 6, 12, 24$) months. To make the presentation tractable, I restrict reported analyses mainly to the 12-month holding period. I calculate holding-period monthly portfolio returns using the method illustrated in Liu and Strong (2006). This method computes monthly portfolio returns over a multimonth holding period by decomposing the multimonth buy-and-hold return, which

Table 1
Descriptive statistics

This table reports descriptive statistics and Spearman rank correlations for the main variables used in the study. MV is market capitalization measured in millions of dollars; B/M is the book-to-market ratio; $LM12$ is the new liquidity measure—the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months; $TO12$ is the average daily turnover over the prior 12 months, where the daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding on that day; $RtoV12$ (in millions) is the liquidity measure of Amihud (2002), which is defined as the daily ratio of the absolute return on a day to the dollar trading volume on that day averaged over the prior 12 months; and $BA12$ is the average daily relative bid-ask spread over the prior 12 months, where daily relative spread is the dollar spread divided by the ask price. Because of data limitations on bid and ask prices, $BA12$ is based on available bid and ask prices over the prior 12 months. Also, $BA12$ is only available for NASDAQ stocks. Panel A presents the results on the sample including all NYSE/AMEX ordinary common stocks over the period 1963 to 2003. At the end of each month from December 1963 to June 2003 (475 months), cross-sectional averages for each variable are calculated over NYSE/AMEX stocks. The reported descriptive statistics are based on these 475 time-series cross-sectional averages. Likewise, at the end of each month from December 1963 to June 2003, the cross-sectional Spearman rank correlations are computed, and the time-series average of those correlations are reported. Also, at the end of each month from December 1963 to June 2003, the number of stocks within five different $LM12$ categories are computed. The time-series average of the number of stocks within each of the five categories are presented. The number of NYSE/AMEX stocks in each month ranges between 1,406 and 2,315 with an average of 1,934. Panel B reports the results for all NASDAQ ordinary common stocks over the period 1983 (when a reasonable number of stocks with trading volume and bid and ask prices become available from the CRSP database) to 2003. At the end of each month from December 1983 to June 2003 (235 months), cross-sectional averages for each variable and Spearman rank correlations are calculated over the sample NASDAQ stocks. The reported statistics for NASDAQ stocks are based on these 235 time-series cross-sectional averages. The number of NASDAQ stocks in each month ranges between 2,523 and 4,375 with an average of 3,489. Note that the results related to the B/M variable are separately determined based on nonnegative B/M and nonfinancial stocks, but there is no such restriction imposed on other variables. Also, the results relating to the $BA12$ measure are separately calculated under the requirement of the availability of bid and ask prices, but there is no such requirement imposed on other variables. For individual stocks, the maximum $LM12$ is 249 within NYSE/AMEX, and it is 251 within NASDAQ.

Panel A: Results for NYSE/AMEX stocks over the period 1963–2003

	MV (\$m)	B/M	$TO12$ (%)	$RtoV12$ (m)	$LM12$
Descriptive statistics					
Mean	1404.3	0.942	0.223	4.19	10.39
Median	714.1	0.890	0.218	2.72	9.31
Spearman rank correlation					
B/M	−0.352	1			
$TO12$	0.111	−0.176	1		
$RtoV12$	−0.944	0.309	−0.321	1	
$LM12$	−0.514	0.243	−0.740	0.665	1
Number of stocks in different LM12 categories					
	$0 \leqslant LM12 < 1$	$1 \leqslant LM12 < 5$	$5 \leqslant LM12 < 21$	$21 \leqslant LM12 < 63$	$63 \leqslant LM12 \leqslant 252$
Mean	1234.93	211.64	214.72	167.58	105.05
Median	1224	204	196	155	98
Min	658	50	87	45	6
Max	1746	420	436	400	358

Table 1 (*continued*)

Panel B: Results for NASDAQ stocks over the period 1983–2003

	MV (\$m)	B/M	$TO12$ (%)	$RtoV12$ (m)	$BA12$	$LM12$
Descriptive statistics						
Mean	320.4	0.852	0.450	13.58	5.012	35.63
Median	179.7	0.791	0.439	10.24	4.927	34.72
Spearman rank correlation						
B/M	−0.431	1				
$TO12$	0.354	−0.331	1			
$RtoV12$	−0.842	0.388	−0.599	1		
$BA12$	−0.851	0.385	−0.504	0.941	1	
$LM12$	−0.612	0.365	−0.819	0.780	0.694	1

Number of stocks in different LM12 categories

	$0 \leqslant LM12 < 1$	$1 \leqslant LM12 < 5$	$5 \leqslant LM12 < 21$	$21 \leqslant LM12 < 63$	$63 \leqslant LM12 \leqslant 252$
Mean	1319.60	385.03	508.81	529.60	746.29
Median	1161	352	524	534	714
Min	575	184	268	326	324
Max	2278	645	722	705	1294

largely avoids the bias due to the bid-ask spread as demonstrated by Blume and Stambaugh (1983). If a stock is delisted in the holding period, its post-delisting monthly returns are assumed to be zero over the remaining holding period. Equivalent results obtain by instead assuming that the post-delisting returns equal the relevant risk-free rates over the remaining holding period. The nonoverlapping monthly portfolio returns over the full test period are calculated based on the technique of Jegadeesh and Titman (1993).

As a robustness check I also examine characteristics-adjusted holding-period performance. That is, the performance of each stock in a portfolio is adjusted against its characteristic(s)-matched benchmark portfolio (either equally or value-weighted). In this study, I consider three characteristics, namely, size (MV), book-to-market (B/M), and turnover ($TO12$), and then consider the three characteristics together. Specifically:

(1) *One-characteristic-matched benchmark portfolio*. To form a MV-matched benchmark portfolio at the beginning of each holding period, I sort all NYSE/AMEX/NASDAQ stocks into 100 portfolios on MV using NYSE breakpoints. The benchmark of stock i is the centile portfolio to which stock i belongs but that excludes stock i. The B/M-matched benchmark and the $TO12$-matched benchmark are similarly constructed, except that the $TO12$-matched benchmark is selected from NYSE/AMEX stocks, and the B/M-matched benchmark is constructed using nonnegative-B/M and nonfinancial NYSE/AMEX/NASDAQ stocks.
(2) *Three-characteristics— MV, B/M, and $TO12$—matched benchmark portfolio*. To construct the three-characteristics-matched benchmark portfolio for stock i at the beginning of a holding period, I independently sort all nonnegative-B/M and

nonfinancial NYSE/AMEX stocks using NYSE breakpoints into four portfolios based on MV, B/M, and $TO12$. The three independent sorts result in 64 intersections (portfolios). Stock i's benchmark is the portfolio to which stock i belongs but that excludes stock i.

4. Evidence of a liquidity premium

In the first subsection, I discuss the test for a liquidity premium. In short, this test sorts stocks into portfolios based on the new liquidity measure; if the least liquid portfolio consistently outperforms the most liquid portfolio, this is evidence of the presence of a liquidity premium. In the second subsection, I present tests that examine the results' robustness. Specifically, I test the results using subsample analysis, risk adjustments, and seasonality and subperiod analyses.

4.1. Performance and characteristics of LMx-classified decile portfolios

Table 2 presents the performance and characteristics of equally weighted decile portfolios formed on the liquidity measure LMx. All three measures, $LM1$, $LM6$, and $LM12$, show a clear and significant liquidity premium with the one exception of the $LM1$-based liquidity premium over the one-month holding period. In moving from the most liquid decile (S) to the least liquid decile (B), the mean portfolio holding-period return increases almost monotonically. Looking at the $LM12$-based results, portfolio $B-S$ reveals significant premiums of 0.846%, 0.745%, 0.682%, and 0.561% per month for 1-, 6-, 12-, and 24-month testing horizons. These results indicate that the liquidity measure $LM12$ predicts stock returns over the next one to 24 months.[8] There is also a relation between $LM12$ and portfolio performance over the past 12 months. The most liquid decile (S) earns the highest return over the past 12 months, and the least liquid decile (B) earns a past 12-month return that is 12.45% ($t=-5.55$) lower than that of S. This evidence is consistent with the volume-related return reversals documented by Campbell et al. (1993).[9] The $LM6$ measure shows a similar premium to the $LM12$ measure over different holding periods. However, the $LM1$-based premium is weak, and it fails to generate a significant premium over the one-month testing period. By looking at the one-month holding-period returns of the $LM1$ decile portfolios, low-$LM1$ stocks, which have high turnover over the prior month (not tabulated), generally have higher returns. This pattern is somewhat consistent with the high-volume return premium. Gervais et al. (2001) find that high (low) trading volume over a day or a week predicts high (low) returns in the

[8] I also examine the value-weighted $LM12$ portfolios over the sample period January 1963 to December 2003. The resulting return difference between the least liquid decile and the most liquid decile is 0.487% ($t=2.25$), 0.497% ($t=2.42$), 0.437% ($t=2.17$), and 0.387% ($t=2.02$) per month for the 1-, 6-, 12-, and 24-month holding periods. Value-weighting generates a weaker liquidity premium. This is likely due to some temporarily illiquid larger-cap stocks included in the least liquid portfolio. The analysis below shows that illiquid stocks tend to be small. Therefore, value-weighting tends to underestimate the liquidity premium. Accordingly, subsequent examination focuses on equally weighted portfolios.

[9] The argument is that risk-averse market makers accommodate order flow from liquidity-motivated traders and are compensated with higher expected return. The greater is the order flow, the greater is the compensation. Accordingly, this liquidity-induced effect on price changes that accompany large volumes tends to be reversed.

Table 2
Performance and characteristics of portfolios sorted by the new liquidity measure

The table reports results for all NYSE/AMEX ordinary common stocks over the period January 1963 to December 2003. At the beginning of each month starting from January 1964, eligible NYSE/AMEX stocks are sorted in ascending order based on their liquidity measures, *LMx*—the standardized turnover-adjusted number of zero daily trading volumes over the prior x months ($x = 1, 6, 12$). Based on each sort, stocks are grouped into ten equally weighted portfolios based on NYSE breakpoints and held for n months ($n = 1, 6, 12, 24$). S denotes the lowest-*LMx* decile portfolio (the most liquid decile), B denotes the highest-*LMx* decile portfolio (the least liquid decile), and $B - S$ denotes the difference between B and S. *HP*12*m* shows the mean return per month of a portfolio over the 12-month holding period, and similarly for *HP*1*m*, *HP*6*m*, and *HP*24*m*. $\bar{r}_{-12}$ is the 12-month buy-and-hold mean return prior to portfolio formation. *TO*12 is the turnover measure at the beginning of the holding period, *RtoV*12 is the return-to-volume measure, and *NoStk* denotes the number of stocks in a portfolio. *CAP*12*m* presents the 12-month holding-period performance (measured on the monthly basis) with the performance of each individual stock in the portfolio being adjusted for its *MV*, *B*/*M* and *TO*12-matched equally weighted benchmark, which is based on the $4 \times 4 \times 4$ independent triple sorts on these three characteristics. Numbers in parentheses are t-statistics. The t-statistics for $\bar{r}_{-12}$ are calculated using Newey–West heteroskedasticity and autocorrelation-consistent standard errors with a time lag of 11. The *B*/*M* ratios are separately determined based on nonnegative *B*/*M* and nonfinancial stocks, but there is no such restriction imposed on other calculations.

	S	*D*2	*D*3	*D*4	*D*5	*D*6	*D*7	*D*8	*D*9	*B*	*B* − *S*
Performance of the LM1-sorted portfolios: measured on a monthly basis											
*HP*1*m*(%)	1.178	1.413	1.457	1.373	1.405	1.288	1.178	1.068	1.023	1.359	0.180
	(3.31)	(4.40)	(4.83)	(4.88)	(5.33)	(5.25)	(5.09)	(4.85)	(4.44)	(5.25)	(0.93)
*HP*6*m* (%)	0.910	1.171	1.210	1.226	1.234	1.204	1.198	1.116	1.226	1.423	0.513
	(2.76)	(3.90)	(4.33)	(4.66)	(4.97)	(5.15)	(5.40)	(5.28)	(5.48)	(5.69)	(2.91)
*HP*12*m* (%)	0.913	1.157	1.183	1.193	1.205	1.199	1.169	1.116	1.251	1.472	0.560
	(2.88)	(3.98)	(4.35)	(4.65)	(4.99)	(5.24)	(5.41)	(5.43)	(5.77)	(6.05)	(3.46)
Performance of the LM6-sorted portfolios: measured on a monthly basis											
*HP*1*m* (%)	0.793	1.181	1.208	1.168	1.181	1.134	1.168	1.232	1.365	1.599	0.806
	(2.21)	(3.75)	(4.21)	(4.47)	(4.96)	(5.14)	(5.29)	(5.24)	(5.17)	(5.81)	(4.06)
*HP*6*m* (%)	0.761	1.118	1.150	1.158	1.119	1.106	1.145	1.211	1.346	1.507	0.746
	(2.23)	(3.71)	(4.21)	(4.62)	(4.92)	(5.22)	(5.46)	(5.39)	(5.34)	(5.78)	(4.13)
*HP*12*m* (%)	0.824	1.097	1.166	1.167	1.132	1.085	1.129	1.228	1.340	1.509	0.685
	(2.51)	(3.73)	(4.35)	(4.75)	(5.05)	(5.25)	(5.59)	(5.63)	(5.44)	(5.97)	(4.10)
Performance of the LM12-sorted portfolios											
*HP*1*m* (%)	0.775	1.117	1.167	1.136	1.182	1.058	1.246	1.236	1.390	1.621	0.846
	(2.12)	(3.59)	(4.12)	(4.55)	(5.23)	(5.01)	(5.57)	(5.02)	(5.16)	(5.87)	(4.40)
*HP*6*m* (%)	0.772	1.085	1.137	1.179	1.097	1.076	1.198	1.227	1.329	1.518	0.745
	(2.24)	(3.63)	(4.20)	(4.88)	(5.02)	(5.30)	(5.66)	(5.14)	(5.12)	(5.80)	(4.25)
*HP*12*m* (%)	0.829	1.093	1.151	1.171	1.103	1.062	1.199	1.244	1.313	1.511	0.682
	(2.51)	(3.74)	(4.36)	(4.92)	(5.10)	(5.34)	(5.82)	(5.36)	(5.19)	(5.94)	(4.19)
*HP*24*m* (%)	0.877	1.110	1.152	1.159	1.104	1.059	1.151	1.249	1.271	1.438	0.561
	(2.80)	(3.99)	(4.56)	(5.01)	(5.25)	(5.44)	(5.77)	(5.60)	(5.24)	(5.90)	(3.76)
$\bar{r}_{-12}$ (%)	27.042	17.197	14.374	13.139	11.931	11.481	12.001	14.378	16.638	14.590	−12.452
	(6.01)	(5.38)	(5.32)	(5.59)	(5.96)	(6.06)	(5.73)	(5.29)	(5.32)	(4.52)	(−5.55)
Characteristics of the LM12-sorted portfolios											
MV($m)	934.8	1220.7	1592.9	2025.1	2178.3	2590.8	2915.9	2588.5	613.3	87.7	−847.1
B/*M*	0.770	0.843	0.835	0.817	0.808	0.785	0.820	0.884	0.948	1.232	0.462
*RtoV*12 (m)	0.224	0.335	0.299	0.309	0.231	0.367	0.520	1.404	2.319	13.154	12.930
*TO*12 (%)	0.664	0.364	0.277	0.221	0.180	0.148	0.136	0.135	0.151	0.107	−0.557
*LM*12	0.000	0.000	0.000	0.000	0.000	0.008	0.179	0.785	3.053	38.368	38.368
NoStk	177.90	156.97	149.93	147.01	144.04	142.52	151.30	169.81	206.47	488.52	310.61
Characteristics-adjusted performance of the LM12-sorted portfolios over the 12-month holding period											
*CAP*12*m*(%)	−0.159	0.049	−0.029	0.005	−0.005	−0.016	−0.037	−0.066	0.022	0.093	0.252
	(−3.22)	(1.28)	(−0.93)	(0.21)	(−0.22)	(−0.69)	(−1.42)	(−2.01)	(0.62)	(3.22)	(4.20)

following month. This indicates that the $LM1$ measure, constructed based on a shorter period of one month, is limited in describing stock liquidity. Another drawback of $LM1$ is that it fails to distinguish some illiquid stocks that have the maximum number of 21 zero daily trading volumes over the prior month (21 trading days), as mentioned earlier. Subsequent analysis mainly focuses on the $LM12$ measure with the 12-month holding period.

Looking at the characteristics of the $LM12$-classified decile portfolios in Table 2, the least liquid decile (B) has, on average, almost two months of zero trading volume days over the prior 12 months. It has the lowest MV and turnover ($TO12$) at the beginning of the holding period, and its B/M and return-to-volume ratio ($RtoV12$) are the highest. The most liquid decile portfolio (S) has the highest $TO12$, as expected, the lowest B/M and $RtoV12$, and the third-lowest MV. While the relations among the five variables presented in Table 2 are clear and consistent with the evidence presented in Table 1, MV, B/M, $RtoV12$, and $TO12$ do not vary monotonically across $LM12$ portfolios. In particular, although MV and $LM12$ are correlated as shown in Table 1, size is not a perfect proxy for liquidity since the most liquid portfolio has the third-lowest MV, indicating that its average constituent is medium-sized.

Because of the significant correlations between the new liquidity measure and a number of firm characteristics at the bottom, of Table 2 I report the characteristics-adjusted performance of the $LM12$ deciles with the 12-month holding period. That is, the holding-period returns of each stock in a portfolio are adjusted against its MV, B/M, and $TO12$-matched equally weighted benchmark portfolio. The performance of the $LM12$ deciles shows that most portfolios do not earn significant profits after adjusting for these three characteristics. However, the liquidity premium remains significant at 0.252% per month ($t = 4.20$) after adjusting for the three characteristics although the reduction in the liquidity premium is apparent compared with the unadjusted premium of 0.682%.[10] I examine a separate control for these characteristics together with past 6-month performance below.

The $LM12$-sorted portfolios within NASDAQ stocks are separately examined with results presented in Table A.2, Panel B in the appendix. An immediate result is that NASDAQ stocks are smaller and less liquid than NYSE/AMEX stocks. The least liquid decile (B) has, on average, 159 zero trading volume days (about 7.5 months) over the prior 12 months. The return difference between B and S is significant at 1.337% ($t = 2.09$), 1.232% ($t = 2.16$), and 0.906% ($t = 1.73$) per month over the 1-, 6-, and 12-month holding periods. The relative bid-ask spread ($BA12$) increases monotonically from S to B, consistent with the high correlation between the new liquidity measure and the bid-ask spread as shown in Table 1. The other four characteristics (MV, B/M, $RtoV12$, and $TO12$) also tend to vary monotonically with the new liquidity measure, which is somewhat different from the observed pattern within NYSE/AMEX stocks. However, this should not be interpreted as conflicting with the evidence of Table 2, as NASDAQ stocks are small compared to NYSE/AMEX stocks. For example, the most liquid decile in Panel B of Table A.2 has the largest MV of \$842 million, which is smaller than the average MV of the most liquid portfolio sorted on NYSE/AMEX stocks in Table 2.

[10]The reduction in liquidity premium is less if I adjust for the value-weighted benchmark portfolio. In addition, using the equally weighted benchmark, the $LM12$-based liquidity premium over the 12-month holding period is 0.518% ($t = 3.20$), 0.480% ($t = 3.28$), and 0.265% ($t = 3.21$) per month after adjusting for the MV-matched benchmark, B/M-matched benchmark, and $TO12$-matched benchmark, respectively.

As shown above, illiquid stocks tend to be small. Thus, the new liquidity measure might proxy for the neglected firm effect of Arbel and Strebel (1982) and Merton (1987) although the two effects are difficult to distinguish from each other empirically. The reason is that a stock may have little trading because many investors are not aware of a small and less visible stock. To show that the new liquidity measure is not simply a proxy for the neglected firm effect, I repeat the above examination using NYSE stocks only. The results are summarized in Table A.2, Panel A in the appendix. It is clear that NYSE stocks are larger and more liquid. However, the return difference between the least liquid decile and the most liquid decile remains highly significant at 0.641% ($t = 3.08$), 0.548% ($t = 2.90$), and 0.470% ($t = 2.65$) per month over the 1-, 6-, and 12-month holding periods. Also, the second-least liquid decile ($D9$) significantly outperforms the most liquid decile by 0.407% per month ($t = 2.70$) over the 12-month holding period. In other words, the liquidity premium is still pronounced after excluding the decile of most infrequently traded stocks, which are most likely to be neglected stocks. These results indicate that, to some extent, the liquidity premium is robust to the neglected firm effect, though this may account for some of the pronounced liquidity premium. These results also imply that the liquidity premium is different from and robust to the price delay premium of Hou and Moskowitz (2005), which is strongly associated with stock visibility and investor recognition. Further, to address microstructure issues associated with low-price stocks such as their occasional extreme returns, I examine the liquidity effect by excluding stocks with prices below \$5 at the beginning of each holding period. The performance and characteristics patterns of the $LM12$-classified portfolios remain intact compared with the full sample case. With the exclusion of low-price stocks, the liquidity premium within NYSE/AMEX stocks over the 12-month holding period is still highly significant at 0.514% per month ($t = 3.12$). Hence, subsequent analysis generally focuses on the sample that includes low-price stocks unless otherwise indicated. The use of NYSE breakpoints should also help mitigate the low-price effect. As Table 2 shows, the number of stocks in the least liquid decile is twice that in any other decile.

4.2. *Robustness tests*

4.2.1. *Subsample analysis*

To further control for firm characteristics, I conduct a subsample analysis on the liquidity premium with the subsamples stratified by four firm characteristics, MV, B/M, $TO12$, and the past 6-month return (r_{-6}). Table 3 reports the results on $LM12$-based quintile portfolio returns within the characteristics-stratified subsamples. The evidence here reveals that all of the return differences between B (the least liquid quintile) and S (the most liquid quintile) are statistically significant except for the high-MV subsample. This exception is consistent with both intuition and previous evidence that shows high-MV stocks are liquid. Accordingly, we should not expect to observe a significant liquidity premium within liquid large-size stocks. The significant liquidity premiums of 0.765% ($t = 4.45$) and 0.360% ($t = 2.19$) per month within the low- and medium-MV subsamples indicate that the size effect cannot entirely explain or proxy for the liquidity effect. The significant liquidity premiums within each turnover-stratified subsample further confirm that the new liquidity measure and the turnover measure are materially different despite the new liquidity measure being turnover-adjusted. The significant liquidity premium within each r_{-6}-stratified subsample again indicates that the new liquidity measure

Table 3
Subsample analysis with portfolios classified by the liquidity measure, $LM12$

This table presents the analysis of subsamples stratified on MV, B/M, $TO12$, and past 6-month buy-and-hold returns (r_{-6}). Each subsample contains one-third of the stocks in the sample at the beginning of each holding period. For instance, for the three MV-based subsamples, the low-MV subsample contains the lowest third of MV stocks at the beginning of each holding period, the medium-MV subsample contains the middle third of MV stocks at the beginning of each holding period, and the high-MV subsample contains the highest third of MV stocks at the beginning of each holding period. Within each subsample, the equally weighted quintile portfolios are formed at the beginning of each month (from January 1964 to January 2003) on the basis of the liquidity measure ($LM12$) and are held for 12 months. The lowest-$LM12$ quintile is the most liquid portfolio (S), and the highest-$LM12$ quintile is the least liquid portfolio (B). In Panel C, $TO12$ stands for the average daily turnover over the prior 12 months. Numbers in parentheses are t-statistics. The sample includes all NYSE/AMEX ordinary common stocks over the period January 1963 to December 2003. For the B/M-stratified subsamples, the analysis is carried out based on nonfinancial and nonnegative B/M stocks.

	Panel A: MV-based subsamples			*Panel B: B/M-based subsamples*		
	Low-MV	Medium-MV	High-MV	Low-B/M	Medium-B/M	High-B/M
S	0.963	0.946	1.003	0.780	1.122	1.238
	(2.65)	(2.82)	(3.52)	(2.34)	(3.78)	(4.05)
$Q2$	1.275	1.284	1.081	1.004	1.114	1.335
	(3.97)	(4.46)	(4.75)	(3.70)	(4.87)	(5.62)
$Q3$	1.411	1.268	1.096	0.920	1.095	1.393
	(4.62)	(5.17)	(5.42)	(4.10)	(5.25)	(5.69)
$Q4$	1.558	1.276	1.014	1.128	1.195	1.468
	(5.31)	(5.72)	(5.44)	(4.75)	(5.10)	(5.32)
B	1.728	1.306	1.061	1.294	1.459	1.789
	(6.63)	(6.27)	(5.67)	(4.84)	(5.83)	(6.73)
$B-S$	0.765	0.360	0.058	0.514	0.337	0.551
	(4.45)	(2.19)	(0.37)	(3.50)	(2.41)	(3.43)

	Panel C: TO12-based subsamples			*Panel D*: *r_{-6}-based subsamples*		
	Low-$TO12$	Medium-$TO12$	High-$TO12$	Low-r_{-6}	Medium-r_{-6}	High-r_{-6}
S	1.091	1.166	0.769	0.579	1.074	1.235
	(5.73)	(4.78)	(2.26)	(1.75)	(3.83)	(4.11)
$Q2$	1.094	1.150	1.010	0.873	1.149	1.317
	(5.68)	(5.11)	(3.30)	(3.20)	(5.20)	(5.47)
$Q3$	1.305	1.239	1.117	0.969	1.169	1.321
	(5.94)	(5.35)	(3.96)	(3.77)	(5.64)	(5.95)
$Q4$	1.475	1.343	1.215	1.073	1.362	1.462
	(6.06)	(5.24)	(4.24)	(3.84)	(5.98)	(5.97)
B	1.621	1.456	1.220	1.429	1.539	1.701
	(6.77)	(5.13)	(4.11)	(4.88)	(6.68)	(6.75)
$B-S$	0.531	0.290	0.451	0.850	0.465	0.466
	(3.28)	(2.14)	(3.80)	(4.94)	(3.43)	(3.23)

captures different information than the commonly used turnover measure, since Lee and Swaminathan (2000) find that turnover only affects future returns among past losing stocks. In addition, statistical inferences drawn from this subsample analysis remain intact after excluding low-priced stocks. Taken together, the results in Table 3 show that the liquidity premium is more pronounced within low-MV, high-B/M, low-turnover, and past-loser stocks, but is not driven by any particular firm characteristic examined in Table 3, consistent with the characteristics-adjusted results presented in Table 2.

4.2.2. Risk adjustment

Panel A of Table 4 shows that the CAPM cannot account for the liquidity premium. In fact, the CAPM's performance is poor with respect to the less liquid portfolios, resulting in a more pronounced liquidity premium of 0.91% per month, relative to the unadjusted one of 0.682%. The market betas are almost monotonically decreasing from the most liquid decile (S) to the least liquid decile (B). To control for the problem of estimating beta due to nonsynchronous trading, Table 4, Panel A also reports the adjusted betas ($\hat{\beta}_{CHMSW}$) using the method of Cohen et al. (CHMSW, 1983). As we can see, while the least liquid decile now has the fifth-highest CHMSW beta of 1.013, the highest CHMSW beta remains with the most liquid decile. The CHMSW betas still cannot account for the performance of the less liquid portfolios and the liquidity premium. This raises the following question: why do the least liquid stocks, which tend to be small and to realize high holding-period returns, appear to be less "risky" than the most liquid stocks, which tend to be larger stocks and to earn low holding-period returns? It is clear that market beta alone (whether adjusted for nonsynchronous trading or not) is not a complete measure of risk, because it does not capture the liquidity risk to which a security is exposed.

Results in Panel B of Table 4 reveal that the liquidity premium is robust to controlling for risk using the Fama–French three-factor model, which cannot explain the performance of the least liquid portfolio and the more liquid portfolios. The pattern of market exposures of the decile portfolios is similar to the pattern of CAPM betas. Both B and S load more heavily on SMB, which is consistent with earlier results that display B has the smallest average MV, while S has the third-smallest average MV. The coefficients on HML show that B has the third-highest loading and S has the lowest loading, meaning that the least liquid portfolio loads more heavily on value stocks than does the most liquid portfolio, again consistent with earlier evidence that indicates B has the highest average B/M and S has the lowest B/M (see Table 2). After excluding low-price stocks, the three-factor-adjusted liquidity premium remains highly significant at 0.703% per month ($t = 5.81$). Note that with the exclusion of low-price stocks, the least liquid decile tends to be less heavily loaded on the size factor than the most liquid decile, implying that the size factor has limited ability to account for the liquidity premium.

4.2.3. Subperiod and seasonality analyses

In this subsection I report in the text on two further analyses of the liquidity premium using $LM12$-sorted decile portfolios with a 12-month holding period. To check whether the previous results might be period specific, I perform an analysis of two subperiods, namely, January 1963 to December 1983 and January 1983 to December 2003. Profitability across deciles is generally lower in the recent subperiod compared with the early 1960s to early 1980s. However, this has no effect on the liquidity premium, and evidence on the liquidity premium is not due to any particular subperiod. The liquidity premium is 0.764% per month ($t = 3.24$) over January 1963 through December 1983 and it is 0.600% ($t = 2.67$) over January 1983 through December 2003. Similar to the full sample period, neither the CAPM nor the Fama–French three-factor model can explain the liquidity premiums in either subperiod. After adjusting for the three Fama–French factors, the liquidity premium

Table 4

CAPM and three-factor-adjusted performances of portfolios classified by $LM12$

At the beginning of each month from January 1964 to January 2003, stocks are sorted in ascending order based on their liquidity measures, $LM12$—the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. Based on each sort, stocks are grouped into equally weighted decile portfolios based on NYSE breakpoints and held for 12 months. S denotes the lowest-$LM12$ decile portfolio (the most liquid decile), B denotes the highest-$LM12$ decile portfolio (the least liquid decile), and $B-S$ denotes the difference between B and S. Panel A presents parameter estimates of the capital asset pricing model (CAPM)

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_{it},$$

and Panel B reports parameter estimates of the Fama–French three-factor model

$$r_{it} - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it},$$

where r_{it} is the return of portfolio i in month t, r_{ft} is the one-month T-bill rate for month t, and the values of the three factors are obtained from Kenneth French's website. Panel A also reports the adjusted betas ($\hat{\beta}_{CHMSW}$) using the method of Cohen et al. (1983), and $\hat{\alpha}_{CHMSW}$ presents the Jensen alpha estimate based on the CHMSW betas. The CHMSW betas are estimated with a 5-month lead and a 5-month lag. The sample includes all NYSE/AMEX ordinary common stocks over the period January 1963 to December 2003. Low-price stocks are those whose prices are less than \$5 at the beginning of each holding period. Numbers in parentheses are t-statistics.

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	B	$B-S$
Panel A: CAPM-adjusted performance											
$\hat{\alpha}$ (%)	−0.327	0.001	0.112	0.173	0.148	0.148	0.287	0.303	0.343	0.584	0.910
	(−1.97)	(0.004)	(0.95)	(1.82)	(1.79)	(1.85)	(2.91)	(2.37)	(2.33)	(3.37)	(6.97)
$\hat{\beta}$	1.395	1.263	1.150	1.065	0.975	0.888	0.883	0.946	1.005	0.917	−0.477
	(38.2)	(42.3)	(44.3)	(51.0)	(53.6)	(50.3)	(40.5)	(33.6)	(30.9)	(24.1)	(−16.6)
R^2	0.752	0.788	0.803	0.845	0.857	0.841	0.774	0.702	0.666	0.547	0.364
CHMSW-beta-adjusted performance											
$\hat{\alpha}_{CHMSW}$ (%)	−0.273	0.052	0.151	0.216	0.187	0.192	0.314	0.297	0.334	0.538	0.811
	(−1.64)	(0.38)	(1.27)	(2.25)	(2.23)	(2.35)	(3.17)	(2.34)	(2.28)	(3.11)	(5.94)
$\hat{\beta}_{CHMSW}$	1.283	1.154	1.068	0.974	0.893	0.797	0.828	0.958	1.024	1.013	−0.270
Panel B: Fama–French three-factor-adjusted performance											
$\hat{a}$ (%)	−0.597	−0.300	−0.160	−0.043	−0.057	−0.029	0.032	−0.037	−0.009	0.199	0.796
	(−5.70)	(−3.70)	(−2.16)	(−0.67)	(−0.94)	(−0.44)	(0.44)	(−0.47)	(−0.11)	(2.14)	(6.16)
$\hat{b}$	1.234	1.172	1.087	1.026	0.977	0.911	0.904	0.921	0.904	0.784	−0.450
	(49.7)	(61.0)	(62.0)	(67.0)	(68.2)	(58.4)	(52.9)	(48.7)	(50.0)	(35.6)	(−14.7)
$\hat{s}$	0.955	0.776	0.641	0.471	0.324	0.212	0.346	0.628	0.894	1.051	0.096
	(27.5)	(28.9)	(26.2)	(22.0)	(16.2)	(9.71)	(14.5)	(23.8)	(35.4)	(34.1)	(2.25)
$\hat{h}$	0.182	0.322	0.316	0.268	0.306	0.295	0.406	0.470	0.382	0.388	0.206
	(5.35)	(12.2)	(13.2)	(12.8)	(15.6)	(13.8)	(17.4)	(18.2)	(15.5)	(12.9)	(4.92)
R^2	0.904	0.927	0.925	0.930	0.926	0.896	0.884	0.887	0.913	0.873	0.396
Fama–French three-factor-adjusted performance after excluding low-price stocks											
$\hat{a}$ (%)	−0.520	−0.257	−0.128	−0.023	−0.020	−0.004	0.054	0.008	0.065	0.182	0.703
	(−4.84)	(−3.01)	(−1.68)	(−0.33)	(−0.32)	(−0.06)	(0.76)	(0.10)	(0.79)	(2.36)	(5.81)
$\hat{b}$	1.238	1.172	1.089	1.033	0.974	0.909	0.892	0.913	0.891	0.760	−0.478
	(48.5)	(57.8)	(60.0)	(63.3)	(65.8)	(56.3)	(52.9)	(46.7)	(45.6)	(41.5)	(−16.7)
$\hat{s}$	0.893	0.681	0.535	0.369	0.250	0.149	0.260	0.490	0.713	0.808	−0.085
	(25.0)	(24.0)	(21.1)	(16.2)	(12.1)	(6.62)	(11.0)	(17.9)	(26.1)	(31.6)	(−2.13)
$\hat{h}$	0.131	0.289	0.281	0.269	0.291	0.279	0.368	0.419	0.349	0.315	0.184
	(3.76)	(10.4)	(11.3)	(12.0)	(14.4)	(12.6)	(16.0)	(15.7)	(13.1)	(12.6)	(4.69)
R^2	0.898	0.915	0.916	0.917	0.917	0.885	0.878	0.868	0.884	0.885	0.483

in the early subperiod is 0.595% ($t = 3.27$) per month, and in the recent subperiod it strengthens to 0.921% ($t = 5.29$) per month.

Based on the relative bid-ask spread measure, Eleswarapu and Reinganum (1993) find that the liquidity premium is reliably positive only during the month of January. I therefore examine the January and non-January performance of the $LM12$-classified decile portfolios. The results reveal strong seasonal patterns. In any sample period, each decile portfolio realizes higher mean returns in January than in non-January months. The least liquid decile shows the largest January returns of 7.286%, 8.823%, and 5.749% for the test periods January 1964 to December 2003, January 1964 to December 1983, and January 1984 to December 2003. The liquidity premiums realized in January are large and significant at 2.484% ($t = 4.01$) over the full sample period, 3.035% ($t = 3.33$) over the early subperiod, and 1.933% ($t = 2.29$) over the recent subperiod.[11] However, the important message for this study is that the liquidity premium is not limited to January. Although the liquidity premiums for the non-January months are much lower than those for the January months, they remain statistically significant at 0.518% ($t = 3.11$), 0.558% ($t = 2.33$), and 0.479% ($t = 2.07$) per month over the full, early, and recent sample periods.

5. A two-factor model: its construction and performance

The previous section documents a significant liquidity premium using the new liquidity measure. The empirical results also show that illiquid stocks tend to be low-MV and high-B/M stocks. Fama and French (1996) argue that the size and book-to-market factors in their three-factor model proxy for financial distress. As illustrated previously, financial distress can be one of the factors that causes a stock to be less liquid. As a result, liquidity risk should be able to capture, to a certain extent, distress risk. Importantly, empirical studies document that the Fama–French three-factor model has limited power to explain variation in asset returns. For example, Brennan et al. (1998) show that the return predictability of many company-specific characteristics including MV and B/M persists after returns are "risk"-adjusted by the three-factor model. These results, the failure of the Fama–French three-factor model to explain the liquidity premium, and the evidence that liquidity risk is a state variable (Pastor and Stambaugh, 2003), motivate me to develop a liquidity-augmented two-factor model. In this section, I first describe the construction of the liquidity factor and verify its validity. Then, I examine the performance of the two-factor model in explaining various pricing anomalies.

5.1. A two-factor model

To construct a liquidity factor, ideally one would follow Pastor and Stambaugh (2003) and construct a market-wide liquidity measure, then use the shock or innovation in market liquidity as the liquidity factor. However, there are two major problems with constructing a liquidity factor in this way. First, it is inappropriate to estimate the liquidity shock using the liquidity measure LMx. For instance, the change in $LM12$ this month compared with the previous month is equivalent to the change in the number of zero daily trading volumes

[11] The large and highly significant January liquidity premium seems to indicate that the observed January effect may be due to liquidity risk. However, this is not the immediate focus of this study. Future research should examine whether liquidity is systematically lower in January.

in this month relative to the number of zero daily trading volumes in the same month of last year, and similarly for *LM*6. While *LM*1 seems to be a good choice to measure the monthly shock in liquidity, it is not an appropriate measure for capturing liquidity mainly due to both the short-term high-volume return premium and its failure to distinguish some illiquid stocks whose daily trading volumes are all equal to zero in the prior month. Second, trading volumes are recorded differently for NYSE/AMEX and NASDAQ stocks. Simply excluding NASDAQ stocks to construct a market-wide liquidity measure may not capture the features of market liquidity accurately, as above we see that less liquid stocks tend to be small stocks, which are the major constituents of NASDAQ. To circumvent these issues in estimating the innovations in market liquidity, I construct a mimicking liquidity factor, *LIQ*, based on the liquidity measure of *LM*12 using NYSE/AMEX/NASDAQ ordinary common stocks. Breeden (1979) shows that mimicking portfolios can replace the state variables in the intertemporal asset pricing model of Merton (1973). A number of studies use mimicking portfolios for economic factors. For instance, Chen et al. (1986) construct mimicking portfolios for several macroeconomic factors, Breeden et al. (1989) adopt them for aggregate consumption growth, and Fama and French (1996) construct their *SMB* and *HML* mimicking portfolios in an attempt to capture distress risk. In the next subsection I provide evidence that market-wide liquidity appears to be a priced state variable, and that the mimicking liquidity factor I construct is able to "hedge" this state risk.

The construction of the mimicking liquidity factor, *LIQ*, is similar to the construction of *SMB* and *HML* in Fama and French (1993), and the momentum factor in Carhart (1997). At the beginning of each month from July 1963 to July 2003, I sort all NYSE/AMEX ordinary common stocks in ascending order based on their liquidity measures, *LM*12. Independently, I sort all NASDAQ ordinary common stocks in ascending order on *LM*12 at the beginning of each month from January 1984 to July 2003. Based on the two independent sorts, I form two portfolios, low-liquidity (*LL*) and high-liquidity (*HL*), as follows:

- Before 1984, *LL* contains the lowest-liquidity NYSE/AMEX stocks based on a 15% NYSE breakpoint. From January 1984 onwards, *LL* contains the lowest-liquidity NYSE/AMEX stocks based on the 15% NYSE breakpoint plus the 35% lowest-liquidity NASDAQ stocks.
- Before 1984, *HL* contains the highest-liquidity NYSE/AMEX stocks based on a 35% NYSE breakpoint. From January 1984 onwards, *HL* contains the highest-liquidity NYSE/AMEX stocks based on the 35% NYSE breakpoint plus the 15% highest-liquidity NASDAQ stocks.[12]

The two portfolios (*LL* and *HL*) are held for six months after portfolio formation. The 6-month holding period is chosen because it gives a moderate liquidity premium compared

[12]The 15% (35%) NYSE breakpoint for finding low-liquidity (high-liquidity) stocks within NYSE/AMEX is equivalent to a 30.66% (28.88%) cutoff within these two exchanges. That is, the 15% to 35% NYSE cutoffs are roughly the same as the NYSE/AMEX 30% to 30% breakpoints used in both Fama and French (1996) and Carhart (1997). The 35% to 15% cutoffs for NASDAQ stocks are chosen because they are smaller and less liquid than NYSE/AMEX stocks (see Table A.2 in the Appendix). In addition, I examine other cutoffs such as 30% to 30% applied to both NYSE/AMEX and NASDAQ. The performance of the liquidity factor (e.g., on *MV*-sorted or *B*/*M*-sorted portfolios) is not sensitive to different breakpoints.

with the 1- and 12-month holding periods (see Table 2), which seems plausible for estimating the liquidity factor. I then construct the liquidity factor as the monthly profits from buying one dollar of equally weighted *LL* and selling one dollar of equally weighted *HL*.[13]

Table 5 summarizes the properties of the mimicking liquidity factor (*LIQ*), and of the market (*MKT*), size (*SMB*), and book-to-market (*HML*) factors for comparison. Over the full sample period (January 1964 to December 2003), *LIQ* has a mean of 0.749% per month ($t = 4.56$), which is more pronounced than for the other three factors. The liquidity factor is also highly significant over the two subperiods. By contrast, both *SMB* and *HML* are insignificant over the recent 20-year period. This evidence suggests that the explanatory power for asset returns of the Fama–French three-factor model is limited. The correlation between *LIQ* and *MKT* is -0.649 over the full period, and it is -0.480 and -0.797 over the early and recent subperiods. The highly negative correlation between the liquidity factor and the market factor reflects the state nature of liquidity: the market is less liquid when it is in downturn states, and investors require higher returns to compensate them for the higher risks they bear in less liquid states (the next subsection provides additional evidence on this). As expected, the correlation between *LIQ* and *HML* is positive at 0.439 over the full period, and *HML* is also negatively correlated with *MKT*. However, the correlation between *LIQ* and *SMB* is -0.145 over the full period, taking an unexpected sign. From the results over the two subperiods, the recent 20-year period drives the negative correlation between *LIQ* and *SMB*. Over the early 20-year period, the correlation between *LIQ* and *SMB* is positive, but it is low at 0.038. The low (and even negative) correlation between *LIQ* and *SMB* accords with earlier results that the most liquid stocks are not the largest ones, and indicates the inability of the size factor to capture the liquidity effect, consistent with the failure of the three-factor model to explain the liquidity premium. This could be the reason why the three-factor-adjusted liquidity premium is enhanced especially over the recent 20-year period.

Both the arbitrage pricing theory (APT) and equilibrium approaches show that asset pricing models have the following form:[14]

$$\mathrm{E}(r_i) = \lambda_0 + \beta_{i1}\lambda_1 + \beta_{i2}\lambda_2 + \cdots + \beta_{iK}\lambda_K, \tag{2}$$

where $\mathrm{E}(r_i)$ is the expected return of asset i, β_{ik} is the beta of asset i relative to the kth risk factor, λ_k is the risk premium of the kth factor ($k = 1, 2, \ldots, K$), and λ_0 is the expected zero-beta rate or risk-free rate (r_f). Accordingly, I construct my two-factor model based on the CAPM plus the factor *LIQ* that captures liquidity risk. The expected excess return of security/portfolio i from the two-factor model is

$$\mathrm{E}(r_i) - r_f = \beta_{m,i}[\mathrm{E}(r_m) - r_f] + \beta_{l,i}\,\mathrm{E}(LIQ), \tag{3}$$

where $\mathrm{E}(r_m)$ is the expected return of the market portfolio, $\mathrm{E}(LIQ)$ is the expected value of the mimicking liquidity factor, and the factor loadings $\beta_{m,i}$ and $\beta_{l,i}$ are the slopes in the

[13]On economic grounds one might argue that we should use the value-weighted market-wide liquidity premium as the liquidity factor. However, this would cause the liquidity factor to be dominated by large-cap stocks, whose liquidity is high. For this reason the aggregate liquidity measure in both Pastor and Stambaugh (2003) and Amihud (2002) is constructed as an equally weighted average of the liquidity measures for individual stocks.

[14]The arbitrage pricing theory is developed by Ross (1976), and the multiple-beta equilibrium model is developed by Merton (1973), Breeden (1979), and Cox et al. (1985). More recently, Fama (1996) explores the relation between expected return and multiple risk factors.

Table 5
Properties of the mimicking liquidity factor

The mimicking liquidity factor (*LIQ*) is constructed as follows. At the beginning of each month from July 1963 to July 2003, all NYSE/AMEX ordinary common stocks are sorted in ascending order based on their liquidity measures, *LM*12—the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. Independently, all NASDAQ ordinary common stocks are sorted in ascending order on *LM*12 at the beginning of each month from January 1984 to July 2003. Then, two portfolios, low-liquidity (*LL*) and high-liquidity (*HL*), are formed. Before 1984, *LL* contains the least-liquid NYSE/AMEX stocks based on a 15% NYSE breakpoint. From January 1984 onwards, *LL* contains the least-liquid NYSE/AMEX stocks based on the 15% NYSE breakpoint plus 35% least-liquid NASDAQ stocks identified with NASDAQ stocks. Before 1984, *HL* contains the most-liquid NYSE/AMEX stocks based on a 35% NYSE breakpoint. From January 1984 onwards, *HL* contains the most-liquid NYSE/AMEX stocks based on the 35% NYSE breakpoint plus the 15% most-liquid NASDAQ stocks. The two portfolios (*LL* and *HL*) are held for six months after portfolio formation. *LIQ* is constructed as the monthly profits from buying one dollar of equally weighted *LL* and selling one dollar of equally weighted *HL*. The average number of stocks in *LL* is 1,194, and the average number of stocks in *HL* is 816. In this table, *MKT*, *SMB*, and *HML* are market, size, and book-to-market factors obtained from Kenneth French's website. Numbers in parentheses are *t*-statistics; numbers in brackets are Wilcoxon statistics.

	MKT	*SMB*	*HML*	*LIQ*
Sample period January 1964–December 2003				
Mean (%)	0.478 (2.32)	0.297 (2.07)	0.351 (2.38)	0.749 (4.56)
Median (%)	0.735 (3.02)	0.200 (1.85)	0.400 (2.76)	0.899 (4.76)
Min (%)	−23.00	−11.60	−20.79	−11.80
Max (%)	16.01	14.62	14.92	14.43
Spearman rank correlation (January 1964–December 2003)				
SMB	0.273	1		
HML	−0.333	−0.190	1	
LIQ	−0.649	−0.145	0.439	1
Sample period January 1964–December 1983				
Mean (%)	0.277 (0.97)	0.537 (2.68)	0.477 (2.80)	0.670 (3.79)
Median (%)	0.355 (1.17)	0.475 (2.79)	0.550 (3.06)	0.738 (3.86)
Spearman rank correlation (January 1964–December 1983)				
SMB	0.414	1		
HML	−0.257	−0.130	1	
LIQ	−0.480	0.038	0.330	1
Sample period January 1984–December 2003				
Mean (%)	0.679 (2.29)	0.058 (0.28)	0.225 (0.94)	0.829 (2.99)
Median (%)	1.135 (3.04)	−0.145 (−0.24)	0.200 (0.96)	1.218 (3.01)
Spearman rank correlation (January 1984–December 2003)				
SMB	0.152	1		
HML	−0.399	−0.265	1	
LIQ	−0.797	−0.299	0.516	1

time-series regression

$$r_{it} - r_{ft} = \alpha_i + \beta_{m,i}(r_{mt} - r_{ft}) + \beta_{l,i} LIQ_t + \varepsilon_{it}. \tag{4}$$

The two-factor model implies that the expected excess return of an asset is explained by the covariance of its return with the market and the liquidity factors. The constant term α_i in Eq. (4) is the risk-adjusted return of asset i relative to the two-factor model. If the two-factor model explains asset returns, the intercept in Eq. (4) should not be significantly different from zero.

5.2. Further verification of the mimicking liquidity factor

This subsection explores three issues, (i) whether market-wide liquidity constructed using the new liquidity measure captures real economic conditions, (ii) whether the mimicking liquidity factor is correlated with the underlying liquidity factor, and (iii) whether liquidity risk is priced, including an examination of the predictability of historical liquidity betas and an estimate of the liquidity risk premium.

5.2.1. Aggregate liquidity

For comparison, I construct four aggregate liquidity measures, namely, one based on the return-to-volume ratio of Amihud (2002), *RtoV*12, one from the turnover measure, *TO*12, and two from the new measures *LM*1 and *LM*12. Market-wide liquidity is the relevant liquidity measure of individual stocks averaged over the sample stocks in the market. The sample includes all NYSE/AMEX ordinary common stocks over the period July 1963 to June 2003. The aggregate *LM*12 measure at the end of month t is

$$ALM12_t = \frac{1}{N_t}\sum_{i=1}^{N_t} LM12_{i,t},$$

where $LM12_{i,t}$ is the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months for stock i at the end of month t, and N_t is the number of eligible NYSE/AMEX stocks at the end of month t. The other three aggregate liquidity measures are computed similarly. The aggregate *LM*1 is denoted by *ALM*1, the aggregate *RtoV*12 by *ARtoV*12, and the aggregate *TO*12 by *ATO*12.

Panel A of Table 6 shows that these aggregate measures are highly correlated, especially over the early subperiod. A high correlation obtains over any sample period for *ALM*12, *ALM*1, and *ARtoV*12. The Spearman correlation between *ALM*12 and *ARtoV*12 is 0.895 over the full sample period. In the early subperiod, July 1963 to June 1983, *ALM*12 is also highly and negatively correlated with *ATO*12 at −0.715. These correlations indicate that the new liquidity measure also captures liquidity features such as price impact and trading quantity at the aggregate level. In relation to *ALM*12, the *ALM*1 measure also does a reasonable job of proxying for aggregate liquidity, and the correlation between the two increases from 0.752 to 0.857 from the early to recent subperiods. This is consistent with the increased trading frequency and turnover in the recent period compared with the early period. The relatively low correlations between *ATO*12 and the other aggregate measures over the full period are driven by the recent subperiod (*ATO*12 almost monotonically increases from August 1991 onwards).

To examine the extent to which market-wide liquidity captures or is affected by real economic conditions, I conduct an analysis of the relation between *ALM*12 and the buy-and-hold return of the value-weighted CRSP NYSE/AMEX/NASDAQ index over the prior 12 months (*Rm*12) over which *ALM*12 is constructed (results not tabulated). I find that the two series are negatively correlated, with a Spearman rank correlation of −0.184 over the period July 1963 to June 2003. A Granger causality test shows highly significant evidence at various lags that *Rm*12 Granger causes *ALM*12, but the converse causation is never significant. The Spearman rank correlation between *ALM*12 and the 6-month lagged

Table 6

Correlations among aggregate liquidity measures, and between traded and nontraded liquidity factors

At the end of each month from July 1963 to June 2003, four aggregate liquidity measures, *ARtoV*12, *ATO*12, *ALM*12, and *ALM*1 are constructed. *ARtoV*12 is the aggregate *RtoV*12 measure, which is the average of *RtoV*12 over all sample stocks. Similarly, *ATO*12 is the aggregate *TO*12 measure, *ALM*12 is the aggregate *LM*12 measure, and *ALM*1 is the aggregate *LM*1 measure. Panel A presents correlations among these aggregate liquidity measures. In Panel B, *MKT*, *SMB*, and *HML* are market, size, and book-to-market factors obtained from Kenneth French's website. *LIQ* is the mimicking liquidity factor, and its construction is described in Table 5. The innovations in market liquidity (*InnML*) are reestimated in each period reported in the table. The sample used to construct the four aggregate liquidity measures and the innovations in market liquidity includes all NYSE/AMEX ordinary common stocks over the period from July 1962 (when the daily trading volume data are available in the CRSP database) to June 2003 (when the trading volume data end in the CRSP 2003 version). Numbers in parentheses are *t*-statistics.

Panel A: Spearman rank correlations among four aggregate liquidity measures

	*ARtoV*12	*ATO*12	*ALM*12
Sample period: July 1963–June 2003			
*ATO*12	−0.310		
*ALM*12	0.895	−0.208	
*ALM*1	0.698	−0.173	0.795
Sample period: July 1963– June 1983			
*ATO*12	−0.845		
*ALM*12	0.889	−0.715	
*ALM*1	0.672	−0.699	0.752
Sample period: July 1983– June 2003			
*ATO*12	−0.073		
*ALM*12	0.917	−0.166	
*ALM*1	0.764	−0.164	0.857

Panel B: Spearman rank correlations among innovations in market liquidity (*InnML*) *and other traded factors*

	MKT	*SMB*	*HML*	*LIQ*
InnML (07/63–06/03)	−0.285 (−6.50)	−0.253 (−5.71)	0.110 (2.43)	0.186 (4.13)
InnML (07/63–06/73)	−0.373 (−4.37)	−0.334 (−3.85)	0.052 (0.56)	0.189 (2.09)
InnML (07/73–06/83)	−0.241 (−2.69)	−0.150 (−1.64)	−0.060 (−0.65)	0.031 (0.33)
InnML (07/83–06/93)	−0.208 (−2.31)	−0.219 (−2.44)	0.299 (3.40)	0.219 (2.44)
InnML (07/93–06/03)	−0.342 (−3.95)	−0.264 (−2.97)	0.148 (1.63)	0.317 (3.63)

*Rm*12 is −0.333 over the period July 1963 to June 2003, and it is −0.321 and −0.416 over the periods July 1963 to June 1983 and July 1983 to June 2003, consistent with the Granger causality test. These results indicate that aggregate liquidity is significantly affected by market conditions: liquidity declines when and after the market performs poorly.

Fig. 1 plots the buy-and-hold market returns over the prior 12 months (*Rm*12) and the negative of the aggregate liquidity measure for *ALM*12. With the negative sign added, a low value for the aggregate measure indicates a low liquidity period, and the two series move in the same direction given their correlation discussed above. Consistent with their correlation, the general tendency of the two time-series plots is to mirror each other either simultaneously or with a time lag. The series identify three large declines in market liquidity, all corresponding to major economic and financial events. First, the market

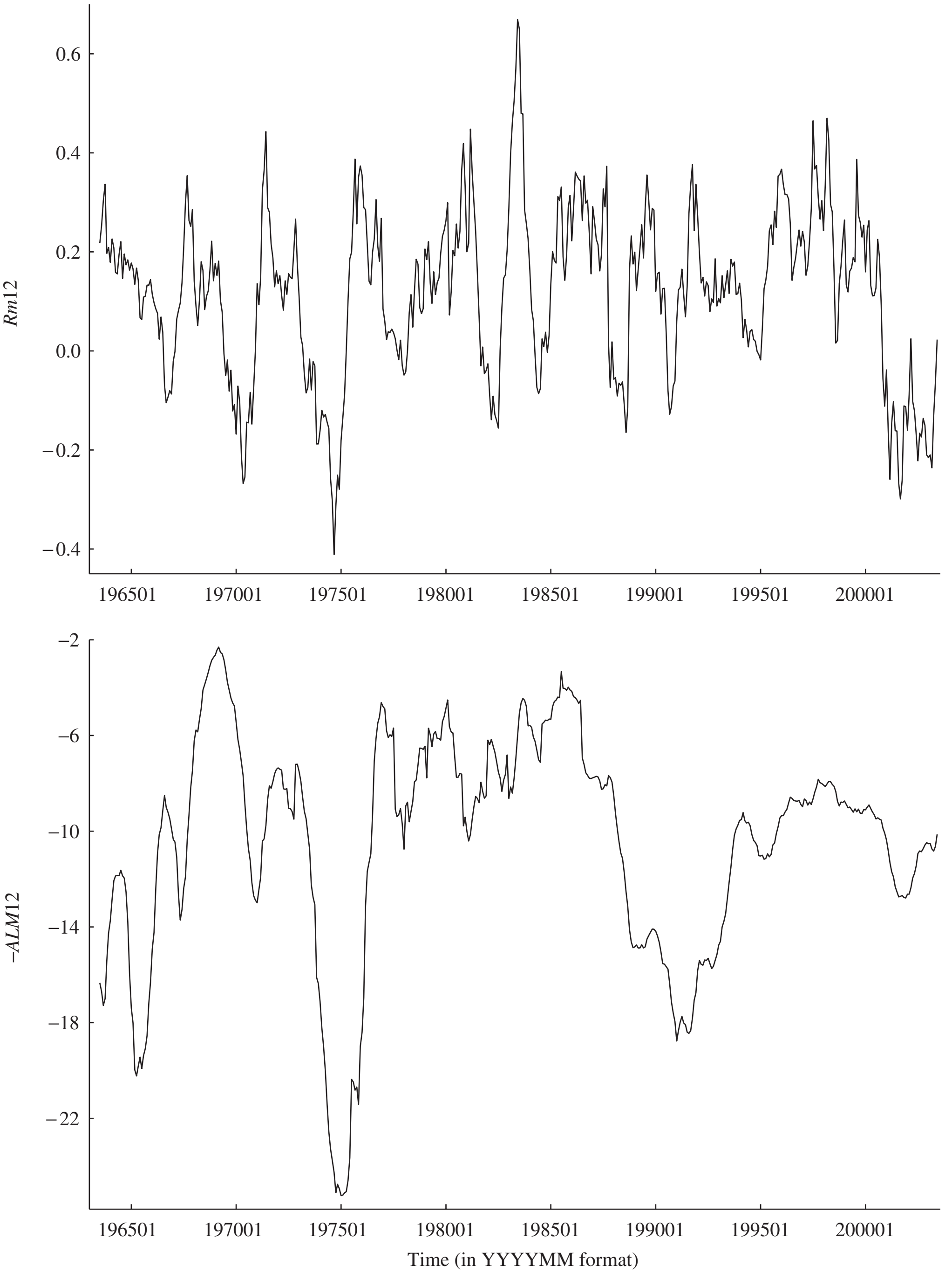

Fig. 1. Aggregate liquidity: *Rm*12 denotes the buy-and-hold return of the value-weighted CRSP NYSE/AMEX/NASDAQ index over the prior 12 months, and $-ALM12$ is the negative $LM12$ measure averaged at the end of each month across NYSE/AMEX stocks. The sample period is from July 1963 to June 2003.

experienced the sharpest and largest tightening in liquidity over the recession of 1972 to 1974, the first large post-World War II economic slowdown, with market liquidity reaching its lowest level during the 40-year sample period in January 1975. This followed several events, including the collapse of the world's monetary system, a four-fold increase in the price of oil, and the political crisis surrounding Watergate. The market records its lowest prior 12-month return of −41.10% at the end of September 1974; whilst the mimicking liquidity factor portfolio earned 16.66% over the same 12 months. Second, following the crash of October 1987, the market suffered a large and continuing decline in liquidity. With the Iraqi invasion of Kuwait on August 2, 1990, and the 1990 Gulf war that followed, market liquidity hit its second-lowest liquidity level since 1970 in January 1991. In response, the Federal Reserve cut the Federal Funds Rate ten times from 6.75% to 4.0% in 1991. While the market fell 22.53% in October 1987 and 9.19% in August 1990, the mimicking liquidity factor value was large at 6.96% in the crash month and 5.73% in August 1990. Third, the market experienced a gradual decline in liquidity from the time the Asian financial crisis began in October 1997 through December 2001. Apart from the Asian financial crisis, the drop in market liquidity coincided with several other events, including the 1998 Russian default and the $3 billion collapse of the US hedge fund Long Term Capital Management, the early 2000 burst of the hi-tech bubble, and the September 11, 2001 terrorist attacks. Market liquidity reached its lowest level since June 1993 in December 2001. Again in response, the Federal Reserve cut the Federal Funds Rate nine times from 6.5% to 2.5% in 2001. The prior 12-month market return reached its lowest value since the 1972 to 1974 recession of −29.88% at the end of September 2001; the mimicking liquidity factor portfolio earned 50.95% over the same 12 months. Besides these major economic events, the time variation in aggregate liquidity ($ALM12$) is also consistent with other events such as the 1976–1978 contraction and the market disruption of 1994. While there are dangers in pushing this hindsight analysis too far, the fact that fluctuations in aggregate liquidity ($ALM12$) coincide with economic conditions provides at least plausible evidence that $ALM12$ exhibits the state nature of capturing market liquidity conditions; moreover, the mimicking liquidity factor LIQ appears to hedge the liquidity state.

5.2.2. Innovation in market liquidity

This subsection estimates the innovation in market liquidity, the underlying liquidity factor, to examine its association with the mimicking liquidity factor. As mentioned earlier, the monthly change in $LM12$ is inappropriate in proxying the monthly shock in liquidity. Thus, I use $LM1$ to estimate the innovation in market liquidity although it is less accurate in describing stock liquidity than $LM12$. Given $ALM1$ is highly correlated with $ALM12$, $LM1$ should be able to serve this verification function although we should not expect to see a substantially high correlation between the $LM1$-based innovation in market liquidity and the mimicking liquidity factor. After all, the correlation between $ALM1$ and $ALM12$ is 0.795, which is even lower than the correlation of 0.895 between $ALM12$ and $ARtoV12$.

The aggregate change in market liquidity at the end of month t is calculated as

$$DALM1_t = \frac{1}{N_t}\sum_{i=1}^{N_t}(LM1_{i,t} - LM1_{i,t-1}), \tag{5}$$

where $LM1_{i,t}$ is the standardized turnover-adjusted number of zero daily trading volumes for stock i in month t, and N_t is the number of eligible NYSE/AMEX ordinary common stocks at the end of month t. I find that the $DALM1$ series is serially correlated over the period July 1963 to June 2003 with a first-order autocorrelation of -0.1413 ($t = -3.13$). Thus, I estimate the innovations in market liquidity as the residuals from the regression

$$DALM1_t = a + bDALM1_{t-1} + u_t. \tag{6}$$

The regression residuals are not serially correlated, with the first-order autocorrelation being -0.009 ($t = -0.19$). I estimate the month-t innovation in market liquidity, $InnML_t$, as the fitted residual divided by 30, that is,

$$InnML_t = \frac{1}{30}\hat{u}_t. \tag{7}$$

The arbitrary scaling factor of 1/30 produces more convenient magnitudes of the innovation-based liquidity betas that I examine in the next subsection. Panel B of Table 6 shows that the innovation in market liquidity (*InnML*) is negatively correlated with the market factor (*MKT*), -0.285 ($t = -6.50$), and positively correlated with *HML*, 0.110 ($t = 2.43$), over the sample period July 1963 to June 2003. These correlations indicate that large innovations (low liquidity shocks) coincide with declines in the market and a high distress premium, some of the liquidity-factor-like features. The negative correlation with *MKT* is consistent over the four 10-year subperiods. The innovation in market liquidity is negatively correlated with the size factor, taking an unexpected sign. These results are all in the same direction as the correlations between the mimicking liquidity factor *LIQ* and the three Fama–French factors (see Table 5).

More importantly, Panel B of Table 6 shows that the mimicking liquidity factor, *LIQ*, is significantly and positively correlated with the innovation in market liquidity at 0.186 ($t = 4.13$) over the sample period July 1963 to June 2003, indicating that large innovations (low liquidity shocks) are accompanied by large liquidity premiums. The significant correlation is also present over three of the four 10-year subperiods, especially over the recent two decades. The exception is the period from mid-1973 to mid-1983, which covers the seven-year period from July 1976 to June 1983 when market liquidity was high and relatively stable. It is not necessary to find a significant correlation over a highly liquid period since high liquidity does not attract a liquidity premium. However, the corollary is that the mimicking liquidity factor should be more closely correlated with the innovation in market liquidity when market liquidity is low, normally following a market downturn. This is indeed the case. Over the three periods associated with large contraction in market liquidity, as summarized in the previous subsection, the Spearman rank correlation between *LIQ* and *InnML* is 0.309 over March 1972 to February 1975, 0.403 over January 1988 to December 1990, and 0.412 over August 1998 to July 2001. Fig. 2 plots the monthly values of the market factor (*MKT*), the negative of *InnML*, and the negative of *LIQ*. With the negative sign added to *InnML*, a low value indicates a low liquidity shock. Adding the negative sign to *LIQ* makes the market factor (*MKT*), the negative of *InnML*, and the negative of *LIQ* move in the same direction. Their co-movements are observable from the plots; they are not perfectly correlated, however.

5.2.3. *The liquidity risk premium*

Aggregate liquidity appears to capture market liquidity conditions, as shown above. Also, the constructed liquidity factor *LIQ* seems to mimic the underlying one. However, is liquidity a priced state variable? If not, including the liquidity factor in Eq. (3) is invalid.

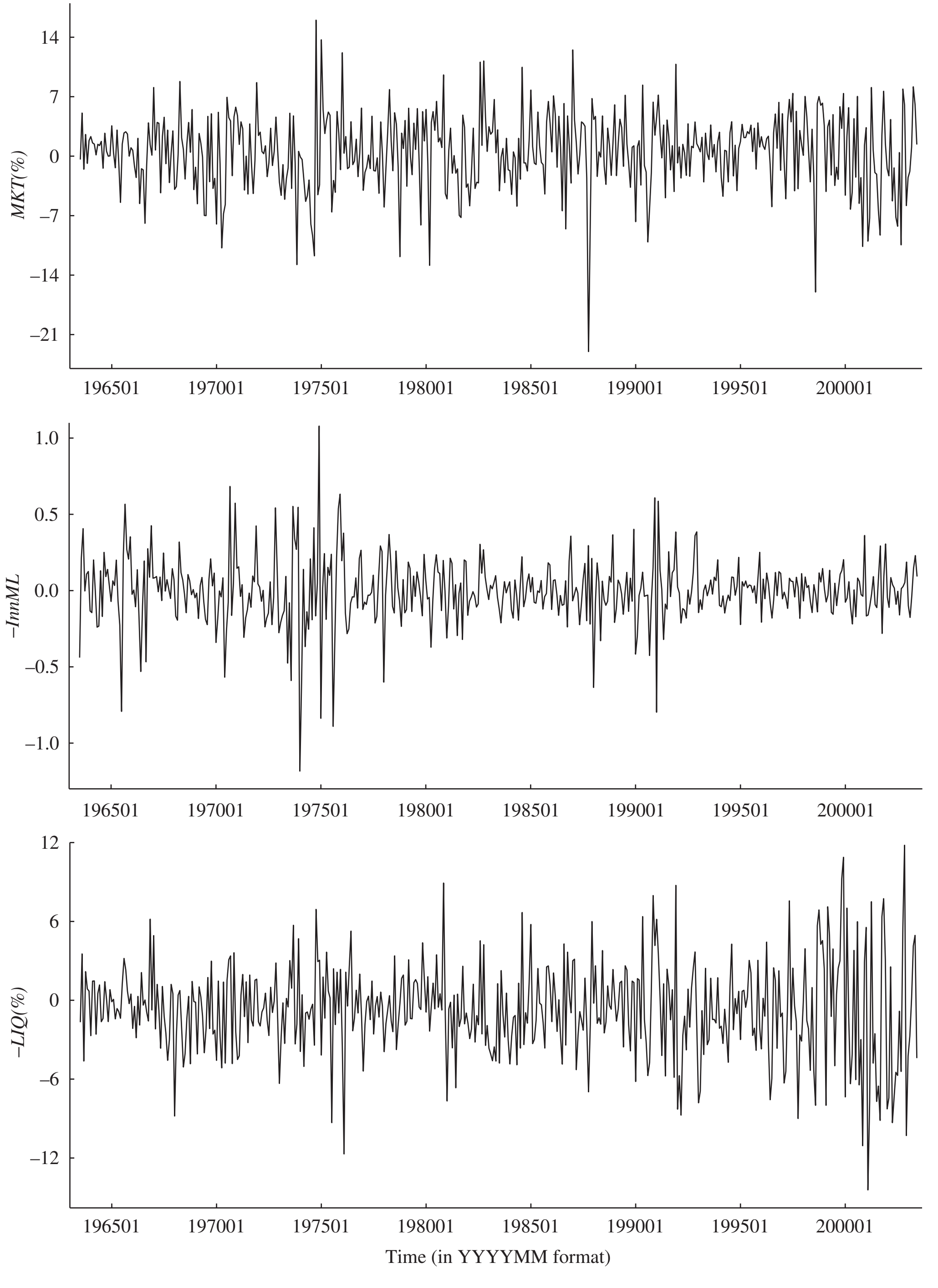

Fig. 2. Innovations in market liquidity and the mimicking liquidity factor: *MKT* is the market factor, $-InnML$ shows the negative innovations in market liquidity, and $-LIQ$ shows the negative mimicking liquidity factor. The sample period is from July 1963 to June 2003.

To answer this question, I examine whether there is a significant liquidity risk premium, that is, the price of liquidity that investors face, by exploring whether high liquidity-risk (high liquidity-beta) stocks outperform low liquidity-risk (low liquidity-beta) stocks.

Specifically, I estimate the historical liquidity betas for all NYSE/AMEX/NASDAQ ordinary common stocks over the period June 1968 to June 2003. To further compare the mimicking liquidity factor (*LIQ*) with the *LM*1-based innovation in market liquidity (*InnML*), I estimate two historical liquidity betas for each sample stock. One is *LIQ*-based, the other *InnML*-based. I estimate the *LIQ*-based historical liquidity betas at the end of each month from running Eq. (4) using prior 5-year (at least 3-year) monthly data. The *InnML*-based liquidity beta for stock i at the end of each month is estimated by running the following time-series regression using prior 5-year (at least 3-year) monthly data:

$$r_{it} - r_{ft} = \alpha_i + \beta_{m,i}(r_{mt} - r_{ft}) + \beta_{l,i} InnML_t + \varepsilon_{it},$$

where the innovations in market liquidity (*InnML*) are re-calculated using Eqs. (6) and (7) at the end of each month based on all prior available data. I find similar results if I base the re-estimations on prior 5-year data.

Panel A of Table 7 shows the results for decile portfolios sorted on *InnML*-based historical liquidity betas. Holding-period returns generally increase from the lowest-beta decile (S) to the highest-beta decile (B). The return difference between B and S is significantly positive over the 1- and 6-month holding periods at 0.389% ($t = 2.73$) and 0.246% ($t = 2.10$) per month, and it is also significant (at 7%) over the 12-month holding period. After adjusting for the CAPM, the return difference between B and S is even higher at 0.434% ($t = 3.07$) per month over the one-month holding period, revealing the inability of the CAPM to capture the liquidity risk. The Fama–French three-factor model performs better than the CAPM (results not tabulated), but its explanatory power is still limited to only some *InnML*-based liquidity-beta portfolios. The characteristics of the *InnML*-based liquidity-beta portfolios show that B/M and $LM12$ generally increase from the lowest-beta to the highest-beta portfolios, indicating that stocks with greater exposure to aggregate liquidity fluctuations are value (distressed) and less liquid stocks. In addition, high liquidity-risk stocks tend to be small with high price-impact (B has the highest $RtoV12$ and the second-lowest MV), and low liquidity-risk stocks are more heavily traded (S has the highest turnover, $TO12$). These liquidity-risk features are generally consistent with intuition. Further, I directly estimate the liquidity risk premium (λ_l) using the GMM estimator based on the post-ranking returns of the ten *InnML*-based liquidity-beta portfolios.[15] The GMM estimates show that high ex ante liquidity-beta portfolios load more heavily on *InnML* in the holding period than do low ex ante liquidity-beta portfolios, and the loading difference between B and S is significant at 1.032. The estimated liquidity risk premium ($\hat{\lambda}_l$) is statistically significant at 0.445% ($t = 2.65$). Note that the magnitude of the estimated liquidity risk premium depends on the arbitrary scaling factor chosen in Eq. (7), which gives the innovation in market liquidity. Nevertheless, scaling does not affect the asymptotic t-statistic or the product $\beta_{l,i}\lambda_l$, which is part of the expected return of asset/portfolio i due to its liquidity risk of $\beta_{l,i}$. The contribution of liquidity risk to $B - S$ is 0.459% per month ($1.032 \times 0.445\%$), which is

[15] The specification of the moment conditions is similar to Pastor and Stambaugh (2003) applied to a two-factor model, where the factors are the market and innovations in market liquidity (based on Eqs. (6) and (7) of this study). The detailed procedure is given by Eqs. (14)–(18) in Pastor and Stambaugh (2003).

Table 7
Performance of portfolios classified by historical liquidity betas

At the beginning of each month starting from July 1968, stocks are sorted into historical liquidity-beta deciles using NYSE breakpoints. Based on each sort, portfolios are equally weighted and held for 1, 6, and 12 months. S denotes the lowest-beta decile and B denotes the highest-beta decile. $HP6m$ shows the mean returns (measured on a monthly basis) over the 6-month holding period, and similarly for $HP1m$ and $HP12m$. $\hat{\alpha}_{CAPM,1m}$ is the estimate of the CAPM intercept for the one-month holding period; MV is the market capitalization at the beginning of the holding period; B/M is the book-to-market ratio; $LM12$ is the new liquidity measure; $TO12$ is the turnover measure; and $RtoV12$ is the return-to-volume ratio. In Panel A, the historical liquidity betas of classifying portfolios are estimated using the two-factor model with nontraded liquidity factor, $InnML$:

$$r_{it} - r_{ft} = \alpha_i + \beta_{m,i}(r_{mt} - r_{ft}) + \beta_{l,i}\, InnML_t + \varepsilon_{it},$$

where $InnML_t$ is the month-t innovation in market liquidity. Panel A also reports the GMM estimates of the liquidity risk premium (λ_l) and the loadings on the market factor and on $InnML$ together with the asymptotic t-statistics. The GMM estimates are determined based on the post-ranking returns of the ten $InnML$-based liquidity-beta portfolios with the one-month holding period. In Panel B, the historical liquidity betas of classifying portfolios are estimated using the two-factor model with traded liquidity factor, LIQ:

$$r_{it} - r_{ft} = \alpha_i + \beta_{m,i}(r_{mt} - r_{ft}) + \beta_{l,i} LIQ_t + \varepsilon_{it},$$

where LIQ_t is the month-t value of the mimicking liquidity factor. The liquidity betas are estimated at the end of each month using prior 5-year (at least 3-year) monthly data, and the innovations in market liquidity are re-estimated using Eqs. (6) and (7) at the end of each month based on all prior available data. The sample includes all NYSE/AMEX/NASDAQ ordinary common stocks, and the testing period is from July 1968 to December 2003. Portfolio B/M ratios are separately determined based on nonnegative B/M and nonfinancial ordinary common stocks. Also, $LM12$, $TO12$, and $RtoV12$ are separately determined under the requirement of 12-month daily trading volume data available prior to portfolio formation. Numbers in parentheses are t-statistics.

	S	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*B*	*B − S*
Panel A: Results of portfolios sorted by InnML-based liquidity beta											
$HP1m$ (%)	1.064	1.290	1.209	1.276	1.278	1.249	1.306	1.284	1.358	1.454	0.389
	(2.92)	(4.40)	(4.49)	(5.01)	(5.16)	(5.10)	(5.22)	(5.00)	(4.95)	(4.09)	(2.73)
$HP6m$ (%)	1.018	1.225	1.213	1.247	1.221	1.198	1.209	1.256	1.264	1.264	0.246
	(2.92)	(4.34)	(4.65)	(5.07)	(5.11)	(5.07)	(5.08)	(5.06)	(4.87)	(3.90)	(2.10)
$HP12m$ (%)	1.041	1.228	1.212	1.234	1.222	1.216	1.203	1.241	1.276	1.239	0.199
	(3.11)	(4.48)	(4.76)	(5.11)	(5.20)	(5.22)	(5.17)	(5.14)	(5.00)	(3.98)	(1.85)
$\hat{\alpha}_{CAPM,1m}$ (%)	0.007	0.304	0.253	0.343	0.358	0.333	0.385	0.356	0.406	0.441	0.434
	(0.03)	(1.95)	(1.87)	(2.70)	(2.87)	(2.71)	(2.98)	(2.62)	(2.71)	(1.83)	(3.07)
MV ($m)	269.2	643.5	862.3	1011.6	1227.9	1289.5	1324.2	1273.6	1123.4	524.4	255.2
B/M	0.952	0.935	0.934	0.936	0.941	0.963	0.973	1.003	1.039	1.076	0.124
$RtoV12$ (m)	8.834	5.288	4.439	4.141	3.978	4.062	4.691	4.774	6.204	13.605	4.771
$TO12$ (%)	0.372	0.285	0.260	0.244	0.233	0.231	0.231	0.241	0.256	0.311	−0.061
$LM12$	15.16	15.21	15.92	16.84	17.64	18.02	18.66	18.46	19.77	22.15	6.99
GMM estimates											
$\hat{\beta}_m$	1.250	1.114	1.037	0.999	0.965	0.954	0.969	0.981	1.031	1.178	−0.073
	(25.8)	(29.8)	(29.0)	(28.1)	(27.6)	(25.7)	(23.8)	(25.5)	(23.2)	(18.4)	(−1.60)
$\hat{\beta}_l$	−0.060	0.196	0.161	0.259	0.349	0.385	0.491	0.443	0.577	0.973	1.032
	(−0.20)	(0.82)	(0.69)	(1.05)	(1.50)	(1.56)	(1.70)	(1.59)	(1.75)	(1.90)	(2.99)
$\hat{\lambda}_l = 0.445\%$ (2.65)											
Panel B: Results of portfolios sorted by LIQ-based liquidity beta											
$HP1m$ (%)	0.824	1.052	1.076	1.229	1.200	1.240	1.400	1.381	1.478	1.510	0.687
	(2.10)	(3.64)	(4.05)	(4.82)	(4.93)	(5.15)	(5.72)	(5.34)	(5.45)	(4.55)	(3.00)
$HP6m$ (%)	0.840	1.034	1.071	1.129	1.187	1.247	1.320	1.326	1.358	1.315	0.475
	(2.27)	(3.69)	(4.16)	(4.61)	(5.02)	(5.37)	(5.55)	(5.43)	(5.25)	(4.22)	(2.34)
$HP12m$ (%)	0.858	1.060	1.091	1.123	1.185	1.219	1.295	1.297	1.337	1.312	0.454
	(2.42)	(3.86)	(4.32)	(4.68)	(5.09)	(5.35)	(5.54)	(5.48)	(5.30)	(4.33)	(2.45)
$\hat{\alpha}_{CAPM,1m}$ (%)	−0.286	0.068	0.123	0.298	0.289	0.337	0.497	0.469	0.559	0.537	0.823
	(−1.21)	(0.46)	(0.94)	(2.29)	(2.32)	(2.67)	(3.70)	(3.09)	(3.32)	(2.35)	(3.77)
MV ($m)	706.3	995.8	1138.1	1133.5	1154.2	1099.0	1020.3	947.3	942.7	678.8	−27.5

Table 7 (*continued*)

	S	D2	D3	D4	D5	D6	D7	D8	D9	B	B − S
B/M	0.789	0.847	0.897	0.923	0.947	0.969	0.998	1.025	1.079	1.169	0.380
$RtoV12$ (m)	5.849	4.252	3.641	3.562	3.284	3.366	4.053	4.678	6.288	15.400	9.551
$TO12$ (%)	0.471	0.309	0.269	0.244	0.227	0.217	0.208	0.205	0.214	0.251	−0.220
$LM12$	7.61	9.17	10.65	12.17	14.04	16.31	19.13	21.37	23.83	29.18	21.58

close to its Jensen α of 0.434%. This contribution is also slightly larger than the raw return 0.389% of $B-S$ due to the negative contribution of market risk ($B-S$ has a market factor loading of -0.073).

Panel B of Table 7 shows that the *LIQ*-based liquidity-beta portfolios have stronger and longer return predictability and their characteristics seem to be more consistent with the liquidity risk features than those in Panel A for the *InnML*-based counterparts. The return differences between B and S are all statistically significant at 0.687% ($t = 3.00$), 0.475% ($t = 2.34$), and 0.454% ($t = 2.45$) per month over the 1-, 6-, and 12-month holding periods. Adjusting for the CAPM again enhances the return difference between B and S to 0.823% per month ($t = 3.77$). The CAPM-adjusted results also indicate that the main contributors to the liquidity risk premium are stocks with high liquidity risk, consistent with expectation. In untabulated estimates, adjusting for the three Fama–French factors leaves the risk premium intact at 0.526% per month ($t = 2.65$) over the one-month holding period. Values of B/M and $LM12$ of the *LIQ*-based liquidity-beta portfolios increase monotonically from the lowest-beta to the highest-beta portfolios, similar to the pattern observed for the *InnML*-based beta portfolios in Panel A. However, the highest-beta portfolio (B) now has the lowest MV and the lowest-beta portfolio (S) has the second-lowest MV, which is the converse of the pattern that obtains for the *InnML*-based beta portfolios. In addition, MV of the lowest *LIQ*-based beta portfolio (\$706.3m) is almost three times its *InnML*-based counterpart (\$269.2m), indicating that low liquidity-risk stocks tend to be somewhat medium-sized, which is similar to the size characteristic of the high-liquidity stocks identified by the new liquidity measure $LM12$ (see Table 2). Overall, the results in Table 7 provide evidence that liquidity risk is priced, that is, investors require higher expected returns for holding stocks with greater exposure to liquidity risk, supporting the inclusion of the liquidity factor in the two-factor model (3). In other words, ignoring the liquidity factor omits an important source of priced risk and contaminates risk measures.

5.3. *Performance of the two-factor model*

This subsection evaluates the performance of the two-factor model, Eq. (3), on portfolios formed on various variables known to be associated with differential average returns such as size (MV), book-to-market (B/M), cashflow-to-price (C/P), earnings-to-price (E/P), dividend yield (D/P), long-term contrarian investment, and intermediate-horizon price momentum. For comparison, I also estimate the CAPM and the Fama–French three-factor model relative to these portfolios. However, before I examine the performance of the two-factor model with respect to these variables, I ask can the two-factor model explain the liquidity effect/risk that the CAPM and the Fama–French three-factor model fail to capture?

Table 8
Two-factor-adjusted performance of portfolios classified by $LM12$, $TO12$, and $RtoV12$

At the beginning of each month from January 1964 to January 2003, stocks are sorted on $LM12$, $TO12$, and $RtoV12$, respectively. Based on each sort, stocks are grouped into equally weighted decile portfolios using NYSE breakpoints and are held for 12 months. S denotes the lowest-$LM12$, lowest-$RtoV12$, and highest-$TO12$ decile portfolio, B denotes the highest-$LM12$, highest-$RtoV12$, and lowest-$TO12$ decile portfolio, and $B-S$ denotes the difference between B and S. $\hat{\alpha}_{CAPM}$ is the intercept estimate of the CAPM, and $\hat{\alpha}_{FF3F}$ is the intercept estimate of the Fama–French three-factor model. The two-factor model is

$$r_{it} - r_{ft} = \alpha_i + \beta_{m,i}(r_{mt} - r_{ft}) + \beta_{l,i}LIQ_t + \varepsilon_{it},$$

where r_{it} is the return of portfolio i in month t, r_{ft} is the one-month T-bill rate for month t, LIQ_t is the liquidity-factor-mimicking portfolio return in month t, and the values on the market factor are from Kenneth French's website. The sample includes all NYSE/AMEX ordinary common stocks. Numbers in parentheses are t-statistics.

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	B	$B-S$
Panel A: LM12-sorted portfolios											
Two-factor adjusted performance over the testing period January 1964–December 2003											
$\hat{\alpha}$ (%)	−0.271	−0.127	−0.058	−0.013	−0.055	−0.073	−0.051	−0.144	−0.116	−0.091	0.180
	(−1.54)	(−0.89)	(−0.47)	(−0.13)	(−0.67)	(−0.92)	(−0.54)	(−1.19)	(−0.81)	(−0.58)	(1.90)
$\hat{\beta}_m$	1.367	1.327	1.236	1.158	1.077	1.000	1.054	1.171	1.237	1.258	−0.108
	(29.1)	(34.8)	(37.7)	(44.7)	(48.7)	(47.3)	(42.1)	(36.3)	(32.4)	(29.8)	(−4.29)
$\hat{\beta}_l$	−0.056	0.129	0.172	0.188	0.206	0.224	0.342	0.452	0.465	0.683	0.739
	(−0.95)	(2.69)	(4.18)	(5.77)	(7.40)	(8.42)	(10.9)	(11.2)	(9.71)	(12.9)	(23.3)
R^2	0.752	0.791	0.810	0.855	0.872	0.861	0.819	0.763	0.721	0.663	0.702
Two-factor adjusted performance over the testing period January 1964–December 1983											
$\hat{\alpha}$ (%)	0.092	0.198	0.225	0.199	0.112	0.005	0.142	0.086	0.176	0.159	0.066
	(0.35)	(0.93)	(1.30)	(1.67)	(1.21)	(0.06)	(1.11)	(0.48)	(0.90)	(0.78)	(0.71)
Two-factor adjusted performance over the testing period January 1984–December 2003											
$\hat{\alpha}$ (%)	−0.284	−0.198	−0.137	−0.096	−0.144	−0.137	−0.152	−0.135	−0.150	0.170	0.114
	(−1.33)	(−1.13)	(−0.82)	(−0.63)	(−1.03)	(−0.99)	(−1.12)	(−0.93)	(−0.80)	(−0.73)	(0.80)
Panel B: TO12-sorted portfolios: testing period January 1964–December 2003											
CAPM- and Fama–French-three-factor-adjusted performance											
$\hat{\alpha}_{CAPM}$ (%)	−0.302	0.039	0.157	0.265	0.280	0.317	0.334	0.344	0.365	0.484	0.786
	(−1.80)	(0.26)	(1.14)	(2.10)	(2.41)	(2.83)	(3.08)	(3.19)	(3.16)	(3.73)	(5.17)
$\hat{\alpha}_{FF3F}$ (%)	−0.575	−0.287	−0.165	−0.029	−0.008	0.036	0.053	0.059	0.066	0.174	0.749
	(−5.63)	(−3.41)	(−2.09)	(−0.38)	(−0.12)	(0.53)	(0.78)	(0.96)	(0.94)	(2.02)	(5.27)
Two-factor (market and liquidity factors) adjusted performance											
$\hat{\alpha}$ (%)	−0.264	−0.140	−0.115	−0.054	−0.068	−0.063	−0.089	−0.051	−0.101	−0.097	0.167
	(−1.48)	(−0.91)	(−0.81)	(−0.42)	(−0.60)	(−0.59)	(−0.90)	(−0.51)	(−0.96)	(−0.86)	(1.23)
$\hat{\beta}_m$	1.371	1.357	1.312	1.274	1.235	1.185	1.155	1.094	1.078	1.041	−0.330
	(28.9)	(33.0)	(34.8)	(37.7)	(40.7)	(41.6)	(43.8)	(40.8)	(38.7)	(34.8)	(−9.06)
$\hat{\beta}_l$	−0.038	0.181	0.276	0.323	0.352	0.384	0.428	0.399	0.471	0.588	0.626
	(−0.63)	(3.50)	(5.82)	(7.62)	(9.26)	(10.7)	(12.9)	(11.9)	(13.5)	(15.7)	(13.7)
Panel C: RtoV12-sorted portfolios: testing period January 1964–December 2003											
CAPM- and Fama–French-three-factor-adjusted performance											
$\hat{\alpha}_{CAPM}$ (%)	−0.037	0.057	0.127	0.099	0.116	0.157	0.157	0.214	0.236	0.492	0.529
	(−0.63)	(0.76)	(1.54)	(1.07)	(1.11)	(1.37)	(1.24)	(1.56)	(1.56)	(2.33)	(2.31)
$\hat{\alpha}_{FF3F}$ (%)	−0.064	−0.076	−0.050	−0.100	−0.129	−0.110	−0.148	−0.113	−0.129	0.040	0.104
	(−1.20)	(−1.14)	(−0.72)	(−1.33)	(−1.70)	(−1.48)	(−2.08)	(−1.66)	(−1.94)	(0.35)	(0.87)
Two-factor (market and liquidity factors) adjusted performance											
$\hat{\alpha}$ (%)	−0.077	−0.042	0.008	−0.049	−0.079	−0.024	−0.071	−0.062	−0.141	−0.234	−0.157
	(−1.24)	(−0.54)	(0.09)	(−0.51)	(−0.73)	(−0.20)	(−0.54)	(−0.45)	(−0.93)	(−1.17)	(−0.70)
$\hat{\beta}_m$	0.991	1.030	1.085	1.125	1.144	1.141	1.178	1.206	1.235	1.384	0.394
	(59.3)	(49.2)	(47.2)	(44.0)	(39.8)	(35.8)	(34.0)	(32.3)	(30.5)	(25.9)	(6.60)
$\hat{\beta}_l$	0.041	0.101	0.121	0.150	0.197	0.184	0.230	0.280	0.382	0.735	0.694
	(1.96)	(3.83)	(4.18)	(4.67)	(5.45)	(4.60)	(5.29)	(5.96)	(7.52)	(11.0)	(9.27)

5.3.1. The two-factor model and the liquidity effect

Table 8 reports estimates of the two-factor model on decile portfolios formed on the new liquidity measure (*LM*12), the turnover measure (*TO*12), and the price-impact measure (*RtoV*12). For the *LM*12 portfolios reported in Panel A, we can see that no abnormal return obtains for any decile portfolios after adjusting for the two factors. The loading on the liquidity factor (*LIQ*) increases monotonically from *S* to *B*, indicating that low-liquidity stocks bear high liquidity risk. The pattern of estimated market factor loadings from the two-factor model is different from the patterns observed in Table 4, where the CAPM and the three-factor model are estimated on *LM*12-classified portfolios. After controlling for liquidity risk, the least liquid portfolio (*B*) has the third-highest market factor loading, indicating that *B* is more sensitive to market movements than the average stock. By contrast, the three-factor model and the CAPM give the lowest and the third-lowest market factor loadings for *B* (see Table 4). Taking the two risk sources (market and liquidity) together, we can conclude that the least liquid portfolio (*B*) is riskier than the most liquid portfolio (*S*).[16] This evidence supports the above assertion that ignoring the liquidity factor contaminates the risk measures. Results for the two subperiods presented in Panel A of Table 8 are similar to the full sample period estimates.

Panel B of Table 8 shows that the performance of the CAPM is poor with respect to low-turnover stocks. The return difference between the lowest-*TO*12 portfolio (*B*) and the highest-*TO*12 portfolio (*S*) is highly significant at 0.786% per month ($t = 5.17$) after adjusting for the CAPM, which is appreciable relative to the unadjusted difference of 0.479% per month (see Panel A of Table A.1 in the Appendix). The Fama–French three-factor model performs better than the CAPM on low-turnover stocks, but it still fails to account for the performance of the lowest-turnover portfolio. In addition, the three-factor model performs worse than the CAPM on high-turnover stocks. Similar to the CAPM, the three-factor adjusted return difference between *B* and *S* is enhanced and highly significant at 0.749% per month ($t = 5.27$). However, the two-factor model performs well across all *TO*12 decile portfolios, and the two-factor adjusted return difference between *B* and *S* is insignificant at 0.167% per month ($t = 1.23$). The loadings on the liquidity factor reveal that the lowest-turnover portfolio is most sensitive to the liquidity factor, and the highest-turnover portfolio bears no significant liquidity risk, consistent with expectations.

Results in Panel C of Table 8 show that the CAPM cannot explain the performance of the highest-*RtoV*12 portfolio (*B*), although it works well for the other *RtoV*12 deciles. The CAPM-adjusted return difference between *B* and *S* remain significant at 0.529% per month ($t = 2.31$), which is only slightly lower than the unadjusted difference of 0.551% (see Panel B of Table A.1 in the Appendix). As mentioned earlier, the three-factor model can account for the *RtoV*12-based liquidity premium since *RtoV*12 is highly correlated with *MV* at −0.944 (see Table 1). The two-factor model performs no worse, and generally better, than either the CAPM or the Fama–French three-factor model. It explains all

[16]Based on Eq. (3), the two-factor model can be expressed as

$$\mathrm{E}(r_i) - \mathrm{E}(r_f) = \left[\beta_{m,i} + \frac{\mathrm{E}(LIQ)}{\mathrm{E}(MKT)}\beta_{l,i}\right]\mathrm{E}(MKT),$$

and the risk of portfolio i can be regarded as the quantity given in the square brackets. From Table 5, the mimicking liquidity factor has an average value of 0.749% per month and the market factor has an average value of 0.478% per month, which implies $\mathrm{E}(MKT)/\mathrm{E}(LIQ) \approx 1.567$. Given this figure, B has a risk exposure of $1.258 + 1.567 \times 0.683 = 2.328$, and S has a risk exposure of $1.367 + 1.567 \times (-0.056) = 1.279$.

*RtoV*12 decile portfolio returns and subsumes the *RtoV*12-based premium. The loadings on both factors (market and liquidity) tend to increase from the lowest-*RtoV*12 portfolio to the highest-*RtoV*12 portfolio, suggesting that high-*RtoV*12 stocks are risker than low-*RtoV*12 stocks.

I also estimate the two-factor model (3) against the liquidity-beta portfolios presented in Table 7. Untabulated results show that the two-factor model accounts for the performance of all innovation-based and *LIQ*-based liquidity-beta decile portfolios. These results and the evidence that the two-factor model can describe the liquidity premiums from different liquidity measures provide further support for the proposed liquidity measure and the liquidity factor.

5.3.2. The two-factor model and the CAPM anomalies

Because the ranking variables I use to test the anomalies hereforwards are not the liquidity measure, I can relax the restriction due to inconsistent records on trading volumes from different exchanges. Accordingly, the various tests below are based on NYSE/AMEX/NASDAQ stocks and use equally weighted decile portfolios with NYSE breakpoints.

Table 9 presents the 12-month holding-period performance and liquidity characteristics of decile portfolios formed on MV and B/M. Panel A of Table 9 shows that, on average, small firms outperform large firms by 0.581% per month ($t = 2.36$) before risk adjustment. After adjusting for the CAPM, the smallest-MV decile still outperforms the largest-MV decile by 0.533% per month ($t = 2.16$). However, after adjusting for the two factors, there is no size effect. The loadings on both factors increase almost monotonically from the largest-MV decile (*S*) to the smallest-MV decile (*B*), indicating that small firms are risker than large firms, and that small firms are less liquid than large firms (*S* has a negative loading on the liquidity factor, indicating large firms are liquid firms). The three-factor model is also able to explain the size effect, as we would expect because it has a size factor. The liquidity measure (*LM*12) of the MV deciles increases monotonically from the largest-MV decile to the smallest-MV decile, consistent with the liquidity factor loadings.[17] The turnover pattern of the MV deciles appears to be an inverse U-shape. Both small and large stocks tend to be less heavily traded than medium-sized stocks. This pattern further indicates that the new liquidity measure is different from the size characteristic since the turnover measure of the *LM*12 decile portfolios decreases almost monotonically from the most liquid to the least liquid portfolios (see Table 2). Given the very high correlation between size and the return-to-volume measure, *RtoV*12 steadily increases when moving from the largest-MV to the smallest-MV portfolios. This evidence together with the result that the two-factor model can explain the size effect is consistent with Amihud (2002), who finds that the size effect is related to changes in market liquidity.

Panel B of Table 9 reveals that before adjusting for risk, the highest-B/M decile (*B*) outperforms the lowest-B/M decile (*S*) by 0.932% per month ($t = 4.62$). Neither the CAPM nor the three-factor model can account for the strong B/M effect. The value premium remains highly significant at 0.518% per month after adjusting for the Fama–French factors. In contrast to the CAPM and the Fama–French three-factor

[17]Although NASDAQ stock trading volumes are inflated relative to those of NYSE/AMEX stocks, *LM*12 can still be used to broadly characterize the liquidity of NYSE/AMEX/NASDAQ stock portfolios sorted on other criteria (e.g., MV, B/M, etc.).

Table 9

Two-factor-adjusted performance of portfolios classified by MV and B/M

At the beginning of each month from January 1964 to January 2003, stocks are sorted in ascending (descending) order based on their B/M ratios (MVs) and grouped into decile portfolios using NYSE breakpoints. The portfolios are equally weighted and held for 12 months. S is the lowest-B/M (biggest-MV) decile portfolio, B is the highest-B/M (smallest-MV) decile portfolio, and $B-S$ is the difference between B and S. $\hat{\alpha}_{CAPM}$ is the intercept estimate of the CAPM, and $\hat{\alpha}_{FF3F}$ is the intercept estimate of the Fama–French three-factor model. $LM12$ is the standardized turnover-adjusted number of zero trading volume days over the prior 12 months at the beginning of the holding period, $TO12$ is the turnover measure, and $RtoV12$ is the return-to-volume ratio. The two-factor model is

$$r_{it} - r_{ft} = a_i + \beta_{m,i}(r_{mt} - r_{ft}) + \beta_{l,i} LIQ_t + \varepsilon_{it},$$

where LIQ_t is the liquidity-factor-mimicking portfolio return in month t. For the MV-classified portfolios in Panel A, the sample includes NYSE/AMEX/NASDAQ ordinary common stocks. For the B/M-classified portfolios in Panel B, the sample includes nonfinancial and nonnegative B/M NYSE/AMEX/NASDAQ ordinary common stocks. Numbers in parentheses are t-statistics.

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	B	$B-S$
Panel A: MV-classified portfolios											
Raw, CAPM- and Fama–French-three-factor-adjusted returns measured on a monthly basis											
Raw (%)	0.898	1.016	1.126	1.132	1.134	1.229	1.279	1.264	1.295	1.480	0.581
	(4.48)	(4.81)	(5.04)	(4.91)	(4.85)	(4.93)	(4.85)	(4.62)	(4.51)	(4.80)	(2.36)
$\hat{\alpha}_{CAPM}$ (%)	−0.049	0.050	0.138	0.134	0.139	0.215	0.247	0.224	0.255	0.485	0.533
	(−1.29)	(0.98)	(2.21)	(1.82)	(1.60)	(2.00)	(1.99)	(1.61)	(1.56)	(2.19)	(2.16)
$\hat{\alpha}_{FF3F}$ (%)	−0.022	−0.023	0.026	0.010	−0.029	0.008	0.011	−0.047	−0.060	0.073	0.094
	(−0.81)	(−0.49)	(0.49)	(0.17)	(−0.56)	(0.17)	(0.23)	(−1.02)	(−1.07)	(0.64)	(0.79)
Two-factor (market and liquidity factors) adjusted performance											
$\hat{\alpha}$ (%)	−0.046	0.038	0.160	0.106	0.119	0.189	0.209	0.116	0.049	−0.122	−0.076
	(−1.15)	(0.70)	(2.41)	(1.36)	(1.29)	(1.67)	(1.59)	(0.79)	(0.29)	(−0.56)	(−0.31)
$\hat{\beta}_m$	0.957	1.004	1.033	1.078	1.069	1.111	1.154	1.206	1.256	1.365	0.408
	(89.6)	(69.9)	(58.3)	(51.8)	(43.4)	(36.6)	(32.8)	(30.9)	(27.5)	(23.3)	(6.17)
$\hat{\beta}_l$	−0.003	0.012	−0.022	0.028	0.020	0.026	0.039	0.109	0.208	0.614	0.617
	(−0.20)	(0.67)	(−0.99)	(1.07)	(0.65)	(0.68)	(0.87)	(2.22)	(3.62)	(8.35)	(7.43)
R^2	0.965	0.943	0.923	0.900	0.864	0.818	0.781	0.750	0.688	0.558	0.106
Liquidity characteristics											
$RtoV12$ (m)	0.013	0.033	0.064	0.093	0.152	0.231	0.372	0.582	1.187	15.945	15.932
$TO12$ (%)	0.236	0.287	0.310	0.316	0.323	0.330	0.332	0.325	0.304	0.233	−0.003
$LM12$	0.113	0.287	0.541	1.203	1.758	2.473	4.153	6.510	11.108	36.244	36.131
Panel B: B/M-classified portfolios											
Raw, CAPM- and Fama–French-three-factor-adjusted returns measured on a monthly basis											
Raw (%)	0.755	0.993	1.101	1.169	1.192	1.308	1.338	1.437	1.560	1.687	0.932
	(2.36)	(3.46)	(4.05)	(4.50)	(4.73)	(5.26)	(5.49)	(5.84)	(6.05)	(5.74)	(4.62)
$\hat{\alpha}_{CAPM}$ (%)	−0.370	−0.079	0.060	0.155	0.201	0.332	0.374	0.481	0.606	0.712	1.081
	(−2.21)	(−0.56)	(0.45)	(1.19)	(1.52)	(2.44)	(2.77)	(3.33)	(3.67)	(3.39)	(5.62)
$\hat{\alpha}_{FF3F}$ (%)	−0.308	−0.150	−0.088	−0.042	−0.022	0.072	0.070	0.135	0.212	0.210	0.518
	(−3.56)	(−2.47)	(−1.59)	(−0.76)	(−0.39)	(1.19)	(1.21)	(2.12)	(2.77)	(1.87)	(4.21)
Two-factor (market and liquidity factors) adjusted performance											
$\hat{\alpha}$ (%)	−0.111	0.019	0.046	0.065	0.074	0.150	0.128	0.154	0.186	0.118	0.229
	(−0.64)	(0.13)	(0.32)	(0.47)	(0.54)	(1.06)	(0.92)	(1.05)	(1.13)	(0.57)	(1.37)
$\hat{\beta}_m$	1.198	1.170	1.161	1.143	1.115	1.112	1.117	1.141	1.184	1.316	0.118
	(25.8)	(29.6)	(30.4)	(31.1)	(30.0)	(29.3)	(30.1)	(29.2)	(26.8)	(23.8)	(2.64)

Table 9 (*continued*)

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	B	$B-S$
$\hat{\beta}_l$	−0.262	−0.099	0.015	0.092	0.128	0.184	0.249	0.331	0.425	0.601	0.862
	(−4.49)	(−2.00)	(0.30)	(1.99)	(2.75)	(3.86)	(5.33)	(6.75)	(7.67)	(8.65)	(15.4)
R^2	0.741	0.766	0.758	0.755	0.734	0.716	0.715	0.691	0.641	0.568	0.399
Liquidity characteristics											
*RtoV*12 (m)	2.755	2.774	2.983	3.391	3.875	4.334	5.106	5.826	8.136	16.814	14.059
*TO*12 (%)	0.444	0.368	0.326	0.298	0.276	0.257	0.237	0.225	0.212	0.212	−0.232
*LM*12	7.010	8.312	9.607	10.953	11.715	13.311	15.585	17.974	22.621	32.170	25.161

model, the two-factor model explains the returns of all B/M decile portfolios. The loadings on the liquidity factor increase monotonically from the lowest-B/M decile to the highest-B/M decile. The lowest-B/M decile has a significantly negative liquidity factor loading, indicating that glamour stocks load heavily on liquid stocks. The highest-B/M decile, i.e., distressed stocks, loads most heavily on illiquid stocks. In addition, B appears to have a higher market factor loading than S. The higher loadings on both factors of the highest-B/M portfolio than the lowest-B/M portfolio reveal that value stocks are risker than growth stocks. The liquidity characteristics show that all three liquidity measures vary monotonically with B/M portfolios. High-B/M stocks are illiquid (large $LM12$), thinly traded (low $TO12$), and suffer from large price impact (high $RtoV12$) compared to low-B/M stocks. In sum, the results in Table 9 show that the two-factor model is able to subsume the size and book-to-market effects.

To further examine the performance of the two-factor model in explaining the value premium, I conduct three more analyses based on different fundamental-to-price ratios, namely, cash-flow-to-price (C/P), earnings-to-price (E/P), and dividend yield (D/P); results are untabulated. Before risk adjustment, both C/P and E/P premiums are significant at 0.435% ($t = 2.86$) and 0.432% ($t = 2.85$) per month over a 12-month holding period. The CAPM cannot account for the C/P and E/P effects. Although the Fama–French three-factor model performs better than the CAPM, it is still unable to subsume the C/P and E/P premiums. Portfolios sorted on dividend yields do not show any significant D/P premium over a 12-month holding period. Even so, the CAPM can only explain the lowest D/P-based decile portfolio return, and the three-factor model fails to account for the performance of the sixth to ninth D/P decile portfolios. However, the two-factor model provides a different story, explaining the returns of all decile portfolios sorted on any of the three variables. Moreover, no C/P, E/P, or D/P premium obtains after adjusting for the market and liquidity factors.

Finally, I examine the long-term (three to five years) contrarian investment strategy documented by DeBondt and Thaler (1985) and the medium-term (three to 12 months) momentum strategy of Jegadeesh and Titman (1993); again, these results are not tabulated. Market risk alone cannot account for contrarian profits. The three-factor model can explain the return difference between past long-term loser and winner portfolios, but its explanatory power is limited in the case of the winner portfolio, which loses significantly after adjusting for the three factors. The two-factor model, however, explains the performance of all decile portfolios formed on past long-term returns, and the two-factor-adjusted contrarian profits are insignificant. Based on the loadings on the market and the liquidity factors, the long-term loser portfolio is significantly riskier than the long-term winner portfolio since the loser portfolio has significantly higher loadings on both factors than does the winner portfolio. Turning to intermediate-horizon momentum strategy with a 6-month holding period, the CAPM can only account for the returns of three deciles from the past 6-month loser decile to the third decile. The Fama–French three-factor model also fails to explain the momentum effect. In fact, it can only account for the performance of three decile portfolios from the third-lowest past 6-month-return decile to the fifth decile. The two-factor model, on the other hand, explains all decile portfolio returns except for the loser and winner portfolios (the loser loses at a 10% significance level). The past 6-month winner's loading on the liquidity factor is lower than that of the loser, but the difference is insignificant. As a result, the liquidity factor cannot explain the momentum profits; however, it gives an improvement relative to the three-factor model.

6. Conclusion

Using a new measure of liquidity for individual securities, namely, the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months, $LM12$, I show that illiquid stocks tend to be small, value, and low-turnover stocks with large bid-ask spreads and large absolute return-to-volume ratios, consistent with the intuitive properties of illiquid stocks. However, the stocks that high $LM12$ identifies as illiquid are not confined to these characteristics. Thus, the new measure is materially different from existing liquidity measures such as turnover, bid-ask spread, etc. In particular, it captures multiple dimensions of liquidity such as trading quantity, speed, and cost, with particular emphasis on trading speed. Based on the new liquidity measure, this paper documents a significant and robust liquidity premium over the sample period 1963 to 2003. The premium is distinct from systematic market risk and the Fama–French three-factor risks. In fact, the liquidity premium is enhanced after adjusting for either the CAPM or the Fama–French three-factor model, indicating that both models fail to capture liquidity risk.

The new measure of aggregate liquidity captures market liquidity conditions. Fluctuations in aggregate liquidity generally correspond to market movements in the expected manner. Large declines in market-wide liquidity obtain following large economic and financial events such as the 1972–1974 recession, the 1987 crash, and the burst of the hi-tech bubble. Further empirical evidence shows that a significant liquidity risk premium exists based on both nontraded and traded liquidity factors, indicating that liquidity risk is priced, and liquidity risk is important for asset pricing. Indeed, the two-factor (market and liquidity) model I develop in this study successfully describes the cross-section of stock returns. It not only captures the liquidity risk that the CAPM and the Fama–French three-factor model fail to explain, but it also provides evidence supporting a liquidity risk-based explanation of various established market anomalies. The size, book-to-market, C/P, E/P, D/P, and long-term contrarian premiums are all explained by the two-factor model. By contrast, the Fama–French three-factor model cannot describe the performance of some portfolios classified by C/P, E/P and D/P, although its explanatory power is generally better than that of the CAPM. The Fama–French three-factor model even fails to account for the B/M effect that it is designed to capture. As Fama and French (1996) point out, their three-factor model may not be able to explain all asset returns, and they advise further work to search for a richer model. The success of the liquidity-augmented two-factor model suggests that liquidity risk is an especially promising direction in this continued search.

Appendix A

Tables A.1 and A.2 show the performance and characteristics of portfolios sorted by *TO*12 and *RtoV*12 with and NYSE/AMEX stocks, and of *LM*12-sorted portfolios with NYSE or NASDAQ stocks.

Table A.1

Performance and characteristics of portfolios sorted by *TO*12 and *RtoV*12

At the beginning of each month from January 1964 onwards, stocks are sorted in descending (ascending) order on *TO*12 (*RtoV*12). Based on each sort, stocks are grouped into equally weighted decile portfolios using NYSE breakpoints and are held for 12 months. *S* denotes the highest-*TO*12 (lowest-*RtoV*12) decile, *B* denotes the lowest-*TO*12 (highest-*RtoV*12) decile, and $B-S$ denotes the difference between *B* and *S*. Panel A reports the results of the *TO*12-sorted portfolios and Panel B reports those of the *RtoV*12-sorted portfolios. *HP*12*m* shows the mean return per month of a portfolio over the 12-month holding period, *LM*12 is the new liquidity measure at the beginning of the holding period, *MV* is the market value, B/M is the book-to-market ratio, and *NoStk* denotes the number of stocks in a portfolio. The sample includes NYSE/AMEX ordinary common stocks over the period January 1963 to December 2003. Numbers in parentheses are *t*-statistics. The reported B/M ratios are separately determined based on nonfinancial and nonnegative B/M stocks; but there is no such restriction on other calculations.

	S	*D*2	*D*3	*D*4	*D*5	*D*6	*D*7	*D*8	*D*9	*B*	$B-S$
Panel A: Results of TO12-sorted portfolios											
Testing period: January 1964– December 2003											
*HP*12*m* (%)	0.852	1.133	1.208	1.287	1.275	1.281	1.273	1.260	1.257	1.331	0.479
	(2.58)	(3.80)	(4.35)	(4.94)	(5.18)	(5.52)	(5.76)	(5.93)	(6.07)	(6.66)	(2.38)
MV ($m)	892.8	1142.0	1423.7	1702.7	1797.2	1892.7	1993.5	1866.2	1431.7	689.0	−203.7
B/M	0.777	0.859	0.880	0.894	0.913	0.920	0.936	0.978	0.989	1.087	0.309
*RtoV*12 (m)	0.706	0.984	1.234	1.617	2.023	2.442	3.035	3.710	5.619	11.972	11.267
*LM*12	0.958	1.630	2.453	3.403	4.389	5.574	6.827	9.300	13.998	36.197	35.239
*TO*12 (%)	0.663	0.369	0.286	0.234	0.196	0.165	0.139	0.113	0.085	0.046	−0.618
NoStk	207.11	182.30	177.42	175.48	174.86	174.54	175.50	182.91	199.92	284.45	77.34
Testing period: January 1964– December 1983											
*HP*12*m* (%)	1.045	1.364	1.411	1.471	1.470	1.461	1.420	1.364	1.298	1.376	0.331
	(2.01)	(2.86)	(3.17)	(3.54)	(3.75)	(3.98)	(4.06)	(4.22)	(4.11)	(4.58)	(1.03)
Testing period: January 1984– December 2003											
*HP*12*m* (%)	0.659	0.903	1.004	1.102	1.080	1.100	1.126	1.157	1.215	1.285	0.626
	(1.62)	(2.51)	(3.03)	(3.50)	(3.62)	(3.87)	(4.15)	(4.19)	(4.53)	(4.86)	(2.61)
Panel B: Results of RtoV12-sorted portfolios											
Testing period: January 1964– December 2003											
*HP*12*m* (%)	0.916	1.015	1.106	1.090	1.105	1.148	1.154	1.213	1.225	1.467	0.551
	(4.41)	(4.73)	(4.90)	(4.65)	(4.63)	(4.71)	(4.59)	(4.71)	(4.68)	(4.97)	(2.42)
MV ($m)	11881.9	2652.3	1405.2	862.4	557.8	365.3	249.3	166.8	101.4	32.1	−11849.8
B/M	0.573	0.709	0.707	0.725	0.764	0.781	0.846	0.902	0.992	1.310	0.737
*TO*12 (%)	0.269	0.285	0.286	0.286	0.267	0.256	0.232	0.208	0.188	0.142	−0.127
*LM*12	0.0056	0.0055	0.028	0.136	0.297	0.711	1.491	2.935	7.596	31.304	31.298
*RtoV*12 (m)	0.006	0.017	0.031	0.054	0.089	0.142	0.227	0.375	0.692	13.644	13.638
NoStk	134.86	135.70	138.15	139.99	142.76	148.53	156.14	168.87	207.55	561.94	427.08
Testing period: January 1964– December 1983											
*HP*12*m* (%)	0.689	0.903	1.012	1.031	1.141	1.253	1.327	1.390	1.411	1.787	1.098
	(2.25)	(2.81)	(3.00)	(2.90)	(3.07)	(3.32)	(3.41)	(3.42)	(3.41)	(3.72)	(3.21)
Testing period: January 1984– December 2003											
*HP*12*m* (%)	1.143	1.127	1.201	1.149	1.068	1.043	0.981	1.036	1.039	1.148	0.005
	(4.07)	(3.94)	(3.99)	(3.75)	(3.56)	(3.37)	(3.07)	(3.27)	(3.23)	(3.34)	(0.02)

Table A.2
Performance and characteristics of portfolios sorted by $LM12$—NYSE and NASDAQ

Panel A reports the results for all NYSE ordinary common stocks over the sample period January 1963 to December 2003. At the beginning of each month starting from January 1964, stocks are sorted in ascending order based on their liquidity measures, $LM12$—the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. Based on each sort, stocks are grouped into equally weighted decile portfolios and held for n months ($n = 1, 6, 12$). S denotes the lowest-$LM12$ decile portfolio (the most liquid decile), B denotes the highest-$LM12$ decile portfolio (the least liquid decile), and $B - S$ denotes the difference between B and S. Panel B presents results for all NASDAQ ordinary common stocks over the period January 1983 to December 2003. In Panel B, the $LM12$-based equally weighted decile portfolios are formed at the beginning of each month starting from January 1984 and are held for 1, 6, and 12 months. The bid-ask spread measure of $BA12$ is determined separately under the requirement that each sample stock must have bid and ask prices available; there is no such restriction imposed on other calculations. In this table, $HP12m$ shows the mean return per month of a portfolio over the 12-month holding period, and similarly for $HP1m$ and $HP6m$. $TO12$ is the turnover measure at the beginning of the holding period; $RtoV12$ is the return-to-volume measure; MV is the market value; and B/M is the book-to-market ratio. Numbers in parentheses are t-statistics. The B/M ratios are separately determined based on nonnegative B/M and nonfinancial stocks, but there is no such restriction imposed on other variables. For the NYSE sample the number of stocks in a portfolio ranges between 99 and 175, with an average of 134. For the NASDAQ sample the number of stocks in a portfolio ranges between 252 and 437, with an average of 348.

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	B	$B - S$
Panel A: LM12-based results of NYSE stocks over the period January 1963–December 2003											
$HP1m$ (%)	0.809	1.145	1.168	1.182	1.209	1.076	1.271	1.248	1.387	1.450	0.641
	(2.29)	(3.77)	(4.25)	(4.85)	(5.44)	(5.16)	(5.97)	(5.56)	(5.65)	(6.09)	(3.08)
$HP6m$ (%)	0.844	1.135	1.149	1.213	1.126	1.084	1.207	1.267	1.337	1.392	0.548
	(2.52)	(3.88)	(4.34)	(5.13)	(5.23)	(5.40)	(5.94)	(5.78)	(5.72)	(6.19)	(2.90)
$HP12m$ (%)	0.902	1.139	1.170	1.203	1.122	1.073	1.179	1.282	1.309	1.372	0.470
	(2.81)	(3.99)	(4.54)	(5.16)	(5.28)	(5.44)	(5.94)	(6.00)	(5.76)	(6.32)	(2.65)
MV ($m)	1057.1	1339.8	1738.9	2212.0	2357.3	2791.0	3248.5	3020.3	800.6	210.3	−846.8
B/M	0.826	0.872	0.852	0.826	0.811	0.788	0.823	0.902	0.979	1.205	0.379
$RtoV12$ (m)	0.129	0.182	0.183	0.172	0.146	0.135	0.273	0.575	1.122	5.699	5.570
$TO12$ (%)	0.665	0.371	0.282	0.226	0.184	0.151	0.132	0.118	0.127	0.096	−0.569
$LM12$	0.000	0.000	0.000	0.000	0.000	0.0063	0.156	0.729	2.901	20.327	20.327
Panel B: LM12-based results of NASDAQ stocks over the period January 1983–December 2003											
$HP1m$ (%)	0.457	0.708	1.003	1.150	1.208	1.258	1.521	1.539	1.871	1.794	1.337
	(0.63)	(1.21)	(1.84)	(2.33)	(2.83)	(3.14)	(3.89)	(4.56)	(6.43)	(8.41)	(2.09)
$HP6m$ (%)	0.409	0.682	0.923	1.178	1.174	1.179	1.465	1.432	1.593	1.640	1.232
	(0.62)	(1.30)	(1.86)	(2.54)	(2.88)	(3.15)	(3.95)	(4.42)	(5.80)	(8.28)	(2.16)
$HP12m$ (%)	0.559	0.765	1.022	1.213	1.194	1.236	1.408	1.389	1.510	1.466	0.906
	(0.91)	(1.53)	(2.14)	(2.69)	(2.98)	(3.36)	(3.99)	(4.45)	(5.70)	(7.71)	(1.73)
MV ($m)	842.3	768.0	711.1	455.2	179.5	107.8	51.9	40.3	30.9	20.5	−821.8
B/M	0.506	0.563	0.651	0.716	0.751	0.795	0.916	1.053	1.174	1.383	0.876
$BA12$ (%)	1.890	2.426	2.750	3.330	3.944	4.732	5.677	6.819	8.000	10.472	8.583
$RtoV12$ (m)	0.167	0.370	0.908	1.894	3.707	6.937	12.283	18.844	30.603	59.503	59.335
$TO12$ (%)	1.597	0.716	0.499	0.404	0.351	0.300	0.257	0.189	0.128	0.066	−1.531
$LM12$	0.000	0.017	0.568	2.527	6.863	14.820	28.818	52.215	90.373	158.542	158.542

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