KOÇ UNIVERSITY-TÜSİAD ECONOMIC RESEARCH FORUM
WORKING PAPER SERIES

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Working Paper 1304
February 2013

KOÇ UNIVERSITY-TÜSİAD ECONOMIC RESEARCH FORUM
Rumelifeneri Yolu 34450 Sarıyer/Istanbul

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This draft: July 03, 2012

Abstract

This paper investigates how the stock market reacts to firm level liquidity shocks. We find that negative and persistent liquidity shocks not only lead to lower contemporaneous returns, but also predict negative returns for up to six months in the future. Long-short portfolios sorted on past liquidity shocks generate a raw and risk-adjusted return of more than 1% per month. This economically and statistically significant relation is robust across alternative measures of liquidity shocks, different sample periods, and after controlling for various risk factors and firm characteristics. Furthermore, the documented effect is stronger for small stocks, stocks with low analyst coverage and institutional holdings, and for less liquid stocks. Our evidence suggests that the stock market underreacts to firm level liquidity shocks, and that this underreaction can be driven by investor inattention as well as illiquidity.

JEL classification code: G02, G10, G11, G12, G14, C13.

Keywords: Stock returns, liquidity shocks, stock market reactions, underreaction, investor attention.

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We thank Yakov Amihud, Andrew Ang, Tarun Chordia, David Hirshleifer, Pete Kyle, Robert Schwartz, Robert Whitelaw, and Wei Xiong for their extremely helpful comments and suggestions. We also benefited from discussions with Reena Aggarwal, Linda Allen, Jim Angel, Bill Baber, Preeti Choudhary, Sandeep Dahiya, Ozgur Demirtas, Allan Eberhart, Pengjie Gao, Olesya Grishchenko, Armen Hovakemian, Levent Guntay, Prem Jain, Paul Kupiec, Yan Li, Yuanzhi Li, Lalitha Naveen, George Panayotov, Lee Pinkowitz, Valery Polkovnichenko, Oleg Rytchkov, Mark Seasholes, Tugkan Tuzun, Haluk Unal, Yuan Wang, Bin Wei, Rohan Williamson, An Yan, Jialin Yu, Yuzhao Zhang, Hao Zhou, and seminar participants at Baruch College, the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve Board, Georgetown University, Temple University, and 2012 Liquidity Risk Management Conference. Turan Bali thanks the Research Foundation of McDonough School of Business, Georgetown University. Lin Peng thanks the PSC-CUNY Research Foundation for financial support. All errors remain our responsibility.

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Abstract

This paper investigates how the stock market reacts to firm level liquidity shocks. We find that negative and persistent liquidity shocks not only lead to lower contemporaneous returns, but also predict negative returns for up to six months in the future. Long-short portfolios sorted on past liquidity shocks generate a raw and risk-adjusted return of more than 1% per month. This economically and statistically significant relation is robust across alternative measures of liquidity shocks, different sample periods, and after controlling for various risk factors and firm characteristics. Furthermore, the documented effect is stronger for small stocks, stocks with low analyst coverage and institutional holdings, and for less liquid stocks. Our evidence suggests that the stock market underreacts to firm level liquidity shocks, and that this underreaction can be driven by investor inattention as well as illiquidity.

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1. Introduction

The liquidity of a stock refers to the degree to which a significant quantity can be traded within a short time frame without incurring a large transaction cost or adverse price impact. It is well documented that the level of individual stock illiquidity is positively priced in the cross-section of expected stock returns.[1] This hypothesis was first proposed by Amihud and Mendelson (1986), who argue that investors demand a premium for less liquid stocks, so that less liquid stocks should have higher average returns.[2]

Liquidity is also time-varying, and subject to persistent shocks.[3] The most recent financial crisis and the heightened focus on liquidity during the crisis show the importance of considering the effect of liquidity shocks on stock returns. Given the documented positive relationship between firm level illiquidity and expected returns, it is reasonable to hypothesize that, when liquidity shocks are persistent (i.e., negative liquidity shocks predict lower future liquidity), investors require a higher risk premium when they are subject to negative liquidity shocks and vice versa. Consequently, as suggested by Amihud (2002), Jones (2002), and Acharya and Pedersen (2005), when security markets react immediately and to the full extent, positive (negative) liquidity shocks should lead to higher (lower) contemporaneous returns and lower (higher) future returns.

This paper investigates how the stock market reacts to firm level liquidity shocks. We find a surprising, positive relation between firm level liquidity innovations and future stock returns: Decile portfolios that go long on stocks with positive liquidity shocks and go short on stocks with negative liquidity shocks generate a monthly raw return of 1.2% in the subsequent month. Furthermore, this economically and statistically significant relation is robust across alternative measures of liquidity shocks and after controlling for various risk factors and firm characteristics such as size, book-to-market, momentum, short-term reversal, analyst dispersion, level of illiquidity, liquidity risk, share turnover, idiosyncratic

[1]See, among others, Amihud and Mendelson (1986, 1989), Brennan and Subrahmanyam (1996), Eleswarapu (1997), Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998), Amihud (2002), and Hasbrouck (2009).

[2]Theoretical studies that investigate the relation between liquidity and asset prices include Amihud and Mendelson (1986), Constantinides (1986), Heaton and Lucas (1996), Vayanos (1998), Duffie, Garleanu, and Pedersen (2000, 2003), Huang (2003), Garleanu and Pedersen (2004), and Lo, Mamaysky, and Wang (2004), among others.

[3]See, for example, Amihud (2002), Chordia, Roll, and Subrahmanyam (2000, 2001), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Jones (2002), and Pastor and Stambaugh (2003).

volatility, and demand for extreme positive returns. Our results are also robust when we restrict the sample to stocks with price greater than $5 or to NYSE-listed stocks, when we use different portfolio weighting schemes, and across various subperiods.

We further investigate the source of this puzzling relation. We first examine the immediate effect of firm level liquidity shocks and find a positive and highly significant contemporaneous relation between liquidity shocks and stock returns. This finding of initial reaction to liquidity shocks is consistent with the argument put forth by the previous literature: a negative and persistent liquidity shock increases future expected illiquidity and therefore should lead to an immediate decrease in stock price due to a higher liquidity risk premium. We then investigate the effect of liquidity shocks in predicting future returns of different holding periods and find that negative liquidity shocks continue to predict negative cumulative returns for up to six months.

This evidence suggests that the market underreacts to firm level liquidity shocks. Although stock prices drop immediately upon negative liquidity shocks, the reaction is not complete. There is a considerable amount of continuation of negative returns and the effects of shocks are not fully incorporated into prices until months later.

We explore two potential driving force of the underreaction: limited investor attention and illiquidity. There has been an increasing body of empirical evidence suggesting that investor inattention can lead to underreaction to information. These studies show that, due to limited investor attention, stock prices underreact to public information about firm fundamentals, such as new products, earnings news, demographic information, innovative efficiency, or information about related firms (e.g., Huberman and Regev (2001), Hirshleifer, Hou, Teoh, and Zhang (2004), Hou and Moskowitz (2005), Hirshleifer, Lim, and Teoh (2009), Hong, Torous, and Valkanov (2007), DellaVigna and Pollet (2007, 2009), Barber and Odean (2008), Cohen and Frazzini (2008), and Hirshleifer, Hsu, and Li (2012)).

Liquidity shocks can be viewed as a type of news on liquidity and it can be triggered by public information releases such as earnings announcements, company events such as stock splits and share buy backs, the return performance of the stocks, sensitivity of stocks to changes in market liquidity, or due to concerns about trading against informed trader in times of heightened uncertainty. Compared to the direct and well-defined information events studied in the previous literature, liquidity shocks are less well defined and its pricing implications are harder to interpret by average investors. The indirect and illusive nature of liquidity news makes it more likely to be ignored by investors and therefore result in significant stock market underreaction to liquidity shocks. Moreover, as argued in the model of Peng and Xiong (2006), an investor who optimizes the amount of attention allocation would allocate more attention to systematic shocks and less to or even completely ignore firm-specific shocks. Thus, a strong case can be made for underreaction to firm level liquidity shocks based on theories of investor attention. The theory further predicts that the degree of underreaction, as measured by return predictability, should be more pronounced for firms that receive less investor attention.

Alternatively, when a stock is harder to trade, its illiquidity may hamper price discovery, which leads to slow price adjustments following liquidity shocks. The illiquidity-based mechanism predicts that the positive return predictability of liquidity shocks should be stronger for the less liquid stocks.

We divide our sample into subgroups based on investor attention proxies and illiquidity and find that the positive link between liquidity shocks and future stock returns is indeed stronger for stocks that receive less attention (small stocks, stocks with low analyst coverage and institutional ownership), as well as for less liquid stocks. To gauge the relative importance of the attention- versus the illiquidity-based mechanisms for underreaction, we employ triple-sorted portfolios that analyze the effect of attention (illiquidity) proxies on underreaction while controlling for illiquidity (attention). In addition, we perform Fama-MacBeth regression analysis and include both attention proxies and illiquidity as interaction variables to liquidity shocks. We find that both the attention proxies and illiquidity help explain the cross-sectional variation in the return predictability of liquidity shocks and these effects are not subsumed by one another. There is also evidence that, while both mechanisms are significant for one month ahead return prediction, the inattention-based mechanism seems to be more important in predicting six-month ahead returns. Our results thus suggest that both investor inattention and illiquidity can drive stock market underreactions to liquidity shocks, and these two mechanisms are distinctly different from each other.

The main liquidity shock variable we employ is constructed as the standardized innovation of the negative Amihud's (Amihud (2002)) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. In addition to this nonparametric standardized liquidity innovation measure, we also construct a conditional measure of liquidity shocks using an ARMA(1,1)-GARCH(1,1) specification.

The Amihud's measure of firm level illiquidity has been used by Acharya and Pedersen (2005) and Chordia, Huh, and Subrahmanyam (2009), among others. This measure is motivated by Kyle's (1985) notion of liquidity, the response of price to order flow (Kyle lambda). By this definition, a stock is considered to be illiquid if a small trading volume generates a large price change. Amihud (2002) shows that this measure is positively and strongly related to Kyle's price impact measure and the fixed-cost component of the bid-ask spread. Hasbrouck (2009) examines a comprehensive set of daily liquidity measures and finds that the Amihud's measure has the highest correlation with the price impact coefficient computed with data on intraday transactions and quotes.

One might argue that innovations in the Amihud's illiquidity measure may be driven by news announcements, i.e., the market makers update prices upon news without much trading, rather than real changes in liquidity. To account for this possibility, we also check the robustness of our findings using an alternative measure of liquidity shocks based on changes in bid-ask spreads. The results are similar to the findings obtained from the changes in the Amihud's illiquidity measure.

Since liquidity shocks can be correlated with several liquidity-related factors that are known to be related to expected returns, we conduct a series of robustness checks to ensure that our findings are not driven by these factors. Brennan and Subrahmanyam (1996), Eleswarapu (1997), Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998), Chordia, Roll, and Subrahmanyam (2001), Amihud (2002) and Hasbrouck (2009) have shown that the firm level illiquidity is an important determinant of expected returns. Chordia, Roll, and Subrahmanyam (2000), Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) argue that systematic liquidity risk is related to expected stock returns. We control for the level of illiquidity as well as systematic liquidity risk and find that our results remain intact. Expected returns can also be affected by the volatility of liquidity if agents care about the risk associated with this variation or take advantage of time varying liquidity. While Chordia, Subrahmanyam, and Anshuman (2001) and Pereira and Zhang (2010) find a negative relation between the volatility of liquidity and the cross-section of expected returns, Akbas, Armstrong, and Petkova (2010) find a positive relationship. Our results remain significant after controlling for the volatility of liquidity.

We also control for other risk factors and firm characteristics that can contribute to the prediction of cross-sectional returns: size and book-to-market (Fama and French (1992, 1993)), price momentum (Jegadeesh and Titman (1993)), short-term reversal (Jegadeesh (1990)), analysts earnings forecast dispersion (Diether, Malloy, and Scherbina (2002)), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006, 2009)), and preference for lottery-like assets (Bali, Cakici, and Whitelaw (2011)). After controlling for a large set of stock return predictors, the positive relation between liquidity shocks and future returns remains highly significant.

Furthermore, we check the robustness of our findings by restricting the original CRSP sample to the NYSE stocks only, by using a subsample of the NYSE, AMEX, and NASDAQ stocks that involves a screen for size and price (Bali and Cakici (2008)), and by eliminating delisted stocks. For the NYSE stocks and for the subsample excluding the smallest, most illiquid, lowest-priced (less than $5 per share), and delisted stocks, the positive cross-sectional link between liquidity shocks and future returns remains intact, implying that it is not small, low-priced, illiquid, and delisted stocks that are driving our results.

The paper contributes to the literature on the effect of investor inattention on stock price dynamics by introducing a new liquidity dimension and by providing evidence that the stock market underreacts to liquidity shocks. In addition, the paper also contributes to the literature on liquidity and stock returns by focusing on the time variation of liquidity and by providing the first piece of evidence of stock market's under-reaction to firm level liquidity shocks. It suggests that liquidity shocks and how the stock market reacts are important in predicting the cross section of future stock returns.

The remainder of the paper is organized as follows. Section 2 provides the data and variable definitions. Section 3 examines the cross-sectional predictive relation between liquidity shocks and stock returns. Section 4 investigates the underlying causes of the asset pricing anomaly. Section 5 provides a battery of robustness checks for our main findings. Section 6 discusses alternative mechanisms for the positive relation between liquidity shocks and future returns. Section 7 concludes the paper.

2. Data

Our sample includes all common stocks traded on the NYSE, Amex, and Nasdaq exchanges, covering the period from July 1963 to December 2010.[4] The daily and monthly return and volume data are from CRSP. We adjust stock returns for delisting in order to avoid survivorship bias (Shumway (1997)).[5] Accounting variables are obtained from the Merged CRSP/Computstat database. Analysts' earnings forecasts come from the I/B/E/S dataset and cover the period from 1983 to 2010. Spreads are calculated using Trade and Quotes (TAQ) tick-by-tick transactions data for the period of 1993-2010. The institutional ownership data are from Thompson 13F filings for the period of 1980-2010.

[4] Amihud (2002), among many others, uses only the NYSE-traded stocks to avoid the effects of difference in market microstructures in influencing the results. We argue that such effects are minimal in our context for they are by and large embedded in the level of illiquidity, and these differences are mostly filtered out in our standardized liquidity shock measure. As such, our main tests are based on the NYSE-, Amex-, and Nasdaq-traded stocks. In the robustness section, we show that our finding remains intact when the tests are confined to the NYSE sample.

[5] Specifically, when a stock is delisted, we use the delisting return from CRSP, if available. Otherwise, we assume the delisting return is -100%, unless the reason for delisting is coded as 500 (reason unavailable), 520 (went to OTC), 551-573, 580 (various reasons), 574 (bankruptcy), or 584 (does not meet exchange financial guidelines). For these observations, we assume that the delisting return is -30%.

2.1. Measures of illiquidity and liquidity shocks

Following Amihud (2002), we measure the illiquidity of a stock i in month t, denoted ILLIQ, as the average daily ratio of the absolute stock return to the dollar trading volume within the month:

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right], \tag{1}$$

where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock i on day d, respectively. A firm is required to have at least 15 daily return observations in month t. The Amihud's illiquidity measure is scaled by 10^6.

A closer investigation of ILLIQ reveals that its volatility is time varying and is positively correlated with the level of illiquidity – the average correlation coefficient between ILLIQ and its monthly volatility, calculated as the standard deviation of daily Amihud illiquidity for that month, is 0.93, and that between ILLIQ and long-term illiquidity volatility, defined as the volatility of monthly ILLIQ over the past 12 months is, 0.74.

To account for the positive correlation between the level and the volatility of illiquidity, we define liquidity shock, denoted LIQU, as the negative difference between ILLIQ and its past 12-month average, and standardize the difference by its volatility as follows:

$$LIQU_{i,t} = -\frac{ILLIQ_{i,t} - AVGILLIQ_{i|t-12,t-1}}{SDILLIQ_{i|t-12,t-1}}, \tag{2}$$

where $AVGILLIQ_{i|t-12,t-1}$ and $SDILLIQ_{i|t-12,t-1}$ are the mean and standard deviation of illiquidity over the past 12 months, respectively. This standardization makes the liquidity shock measure comparable in the cross section as well as in the time series when the volatility of liquidity varies across firms and over time.[6] In the robustness section, we use a more sophisticated, parametric ARMA(1,1)-GARCH(1,1) model to extract a conditional measure of liquidity shock.

[6] According to equation (2), positive (negative) liquidity shock indicates an increase (decrease) in liquidity relative to its past 12-month average.

2.2. Control variables

We employ a large set of control variables in our cross-sectional asset pricing tests. Unless otherwise stated, all variables are measured as of the end of portfolio formation month (i.e., month t), and a minimum of 15 daily observations are required for all variables computed from daily data within a month.

Following Fama and French (1992), market beta of an individual stock is estimated by running a time-series regression based on the monthly return observations over the prior 60 months if available (or a minimum of 24 months):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^1 \left(R_{m,t} - R_{f,t}\right) + \beta_i^2 \left(R_{m,t-1} - R_{f,t-1}\right) + \varepsilon_{i,t}, \tag{3}$$

where R_i, R_f, and R_m are the monthly returns on stock i, the one-month Treasury bills, and the CRSP value-weighted index, respectively. The firm's market beta is the sum of the slope coefficients of the current and lagged excess market returns (i.e. BETA= $\widehat{\beta_i^1} + \widehat{\beta_i^2}$).

The firm's size (LNME) is computed as the natural logarithm of the product of the price per share and the number of shares outstanding (in million dollars). Following Fama and French (1992, 1993, and 2000), the natural logarithm of the book-to-market equity ratio at the end of June of year t, denoted LNBM, is computed as the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock for the last fiscal year end in $t-1$, scaled by the market value of equity at end of December of $t-1$. Depending on availability, the redemption, liquidation, or par value (in that order) is used to estimate the book value of preferred stock.

Following Jegadeesh and Titman (1993), momentum (MOM) is the cumulative return of a stock over a period of 11 months ending one month prior to the portfolio formation month. Following Jegadeesh (1990), short-term reversal (REV) is defined as the stock return over the prior month.

Following Harvey and Siddique (2000), the firm's monthly co-skewness (COSKEW) is defined as the estimate of γ_i in the regression using the monthly return observations over the prior 60 months (if at least 24 months are available):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - R_{f,t}\right) + \gamma_i \left(R_{m,t} - R_{f,t}\right)^2 + \varepsilon_{i,t}, \tag{4}$$

where R_i, R_f, and R_m are the monthly returns on stock i, the one-month Treasury bills, and the CRSP value-weighted index, respectively.

Following Ang, Hodrick, Xing, and Zhang (2006), the monthly idiosyncratic volatility of stock i (IVOL) is computed as the standard deviation of the residuals from the regression:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i \left(R_{m,d} - R_{f,d}\right) + \gamma_i SMB_d + \varphi_i HML_d + \varepsilon_{i,d}, \tag{5}$$

where $R_{i,d}$, $R_{f,d}$, and $R_{m,d}$ are, respectively, the daily returns on stock i, the one-month Treasury bills, and the CRSP value-weighted index. SMB_d and HML_d are the daily size and book-to-market factors of Fama and French (1993).

Following Bali, Cakici, and Whitelaw (2011), the firm's extreme positive return (MAX) is defined as its maximum daily return in a month.

Following Diether, Malloy, and Scherbina (2002), analyst earnings forecast dispersion (DISP) is the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast.

We also control for a variety of liquidity-based variables. In addition to the Amihud's illiquidity measure, we also control for its mean over the past 12 months, *MILLIQ*. Following Pastor and Stambaugh (2003), the firm's liquidity exposure (PS) is the OLS estimate of β_i^L in the regression, estimated using all data available over the past 60 months (if at least 36 months are available):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \varepsilon_{i,t}, \tag{6}$$

where R_i and R_f are the monthly returns on stock i and the one-month Treasury bills, respectively. L is the innovation in aggregate liquidity factor, and MKT, SMB, and HML are the three factors of Fama and French (1993).[7]

Following Chordia, Subrahmanyam, and Anshuman (2001), the trading activity (SDTURN) is computed as the standard deviation of monthly turnover (TURN) over the past 12 months. Following Akbas, Armstrong, and Petkova (2010), the coefficient of variation in the Amihud illiquidity (CVILLIQ) is computed as the standard deviation of the daily Amihud's illiquidity measure in a month scaled by the monthly Amihud's illiquidity measure. In addition to SDTURN and CVILLIQ, we also control for the volatility of the Amihud's illiquidity measure (SDILLIQ), computed as the standard deviation of monthly Amihud's illiquidity over the past 12 months.

In Section 4, we investigate the pricing effect associated with liquidity shocks in conjunction with alternative measures of investor attention. Following the literature, we use several measures to capture the degree of investor attention: (*i*) firm size (LNME); (*ii*) analyst coverage (CVRG), computed as the natural logarithm of the number of analysts covering the firm in the portfolio formation month; and (*iii*) institutional holdings (INST), defined as quarterly institutional ownership as of the portfolio formation month.[8]

[7] Innovations in aggregate liquidity factor are downloaded from Robert Stambaugh's website, and the three factors of Fama and French (1993) are downloaded from Kenneth French's online data library.

[8] Following Cremers and Nair (2005), INST is set to zero if missing in the database.

2.3. Summary statistics

For liquidity shocks to predict future stock returns, a precondition is that the shocks have to be persistent. We first examine the time series properties of firm level illiquidity and find that the ILLIQ variable is highly auto-correlated with an average AR(1) coefficient of 0.72 across all firms over the full sample period. This persistence is consistent with evidence established in the previous literature and implies that a negative liquidity shock leads to lower levels of liquidity (or higher levels of illiquidity) in the future.

Panel A of Table 1 provides the time-series averages of the cross-sectional descriptive statistics for the aforementioned variables. Consistent with improved market liquidity over time, the median liquidity shock (LIQU) is 0.14 over our sample period. On the other hand, the mean liquidity shock is -0.19. The average skewness and kurtosis of liquidity shocks are -1.66 and 4.29, respectively. These statistics suggest that, although there are more firms that experience positive liquidity shocks (increases in liquidity) than those that experience negative liquidity shocks (decreases in liquidity), there are more outliers in the left tail of the liquidity shock distribution and thus the likelihood of large negative liquidity shocks is greater than large positive liquidity shocks. Liquidity shocks also show substantial variation with an average standard deviation of 1.41, almost eight times the mean. To provide a visual description of the monthly illiquidity level and liquidity shocks, we present time-series plots of ILLIQ and LIQU variables for both the CRSP and NYSE samples.

Figure 1 presents the cross-sectional medians of the monthly Amihud's illiquidity measure based on the CRSP sample (the upper panel) and the NYSE sample (the lower panel). The aggregate measure of illiquidity presents strong time-series variation and persistence over the full sample period from August 1963 to December 2010. A notable point in Figure 1 is that stock market illiquidity was very high during the 1970s recession. Especially during the 1973-1975 period, there is a spike that corresponds to several major economic and political events. During the January 1973-December 1974 bear market, all the major stock markets in the world experienced one of the worst downturns in modern history. The crash came after the collapse of the Bretton Woods system over the previous two years, with the associated Nixon shock and the US dollar devaluation under the Smithsonian Agreement. It was compounded by the outbreak of the 1973 oil crisis in October of that year.

Figure 2 shows the cross-sectional medians of the monthly illiquidity measures for the post decimalization period, January 2000-December 2010. In 2000 the Securities and Exchange Commission (SEC) ordered U.S. equity markets to quote prices in decimal increments rather than fractions of a dollar, and the switch was completed by April 9, 2001. The resulting reduction in the minimum tick size has been argued to have contributed to a significant reduction of trading costs. Figure 2 presents a significant decline in the aggregate measure of illiquidity for the post decimalization period. Another notable point in Figure 2 is that there is a sharp increase in stock market illiquidity during the recent financial crisis period from July 2007 to March 2009.

The top panel of Figure 3 depicts the cross-sectional medians of liquidity shocks (LIQU), which shows significant time-series variations. Similar to our findings for the level of illiquidity, in Figure 3 we observe significant negative liquidity shocks during the 1970s recession, the 1987 stock market crash, and the recent Credit Crunch (July 2007-March 2009).

Panel B of Table 1 reports the time-series averages of the cross-sectional correlation coefficients for the control variables. The correlation coefficient between liquidity shocks (LIQU) and one month ahead stock returns (RET) is 3% and significant at the 1% level. Consistent with the hypothesis that a negative and persistent liquidity shock increases the future risk premium and lowers the contemporaneous stock price, the correlation coefficient between LIQU and the contemporaneous stock return (REV) is 16% and highly significant. LIQU is highly correlated with many contemporaneous variables that are commonly controlled for in cross-sectional asset pricing studies. It is significantly negatively correlated with illiquidity level (ILLIQ), illiquidity volatility (CVILLIQ), and return volatility (IVOL), while significantly positively correlated with size (LNME), momentum (MOM), and share turnover (TURN).

3. Cross-sectional Relation between Liquidity Shocks and Stock Returns

The significantly positive correlation between liquidity shocks and future stock returns suggests that negative liquidity shocks (reductions in liquidity) are related to lower cross-sectional stock returns. In this section, we perform formal analysis, and show that the pricing effect documented in this paper cannot be explained by other risk factors and firm characteristics that are known to predict future stock returns in the cross-section.

3.1. Univariate portfolio-level analysis

We begin our empirical analysis with univariate portfolio sorts. For each month, we first sort all stocks trading at NYSE/AMEX/NASDAQ into decile portfolios based on their liquidity shocks, and compare the performance of high LIQ-shock portfolio to low LIQ-shock portfolio in the following month. Decile portfolios are formed every month from July 1963 to November 2010 (in other words, we predict one-month ahead returns covering the period of August 1963 to December 2010) by sorting stocks based on their past month liquidity shocks (denoted by LIQU), where Decile 1 contains stocks with the lowest LIQU, and Decile 10 contains stocks with the highest LIQU.

Table 2, Panel A reports the average next month returns, 3-factor Fama and French (1993) alphas, average monthly liquidity shock (LIQU), average monthly illiquidity level (ILLIQ), and the average market share of each of these LIQU-sorted deciles.

By construction, moving from Decile 1 to Decile 10, the average liquidity shock (LIQU) increases from -3.39 to 1.47, implying that stocks in the lowest LIQU decile (Decile 1) have negative liquidity shocks (i.e., decrease in the level of liquidity), whereas stocks in the highest LIQU decile (Decile 10) have positive liquidity shocks (i.e., increase in the level of liquidity). We also report the portfolio illiquidity level, computed by averaging illiquidity across all firms within the same portfolio. Consistent with the negative correlation between illiquidity level and shock as shown in Table 1 (Panel B), portfolio illiquidity level decreases from the lowest to the highest LIQU portfolios.

More importantly, the average raw return on the LIQU portfolios increases almost monotonically from 0.35% to 1.58% per month. Effectively, the average raw return difference between Decile 1 and 10 (i.e., high LIQU vs. low LIQU) is 1.23% per month with a Newey-West (1987) t-statistic of 5.86.[9] This result indicates that stocks in the highest LIQ-shock decile generate about 15% more annualized returns compared to stocks in the lowest LIQ-shock decile.

In Panel A of Table 2, we also compute the alphas of each liquidity shock decile by regressing the monthly excess returns of the liquidity shock portfolios on the Fama-French's three factors (MKT, SMB, HML) and check if the intercepts from these regressions (namely, 3-factor alpha) are statistically significant. The second column in Panel A, Table 2 shows that as we move from Decile 1 to Decile 10, the 3-factor alphas on the liquidity shock portfolios increase almost monotonically from -0.94% to 0.48% per month. Note also that the 3-factor alphas are statistically significant for both high ILLIQ-shock and low ILLIQ-shock portfolios.

We also check whether the significant return difference between high liquidity shock and low liquidity shock deciles can be explained by the three factors of Fama-French (1993). To do this, we regress the monthly time series of return differences between high liquidity shock and low liquidity shock deciles on the three factors of Fama-French, and we check if the intercept from this regression is statistically significant. As shown in Panel A of Table 2, the 3-factor alpha difference between Deciles 10 and 1 is 1.42% per month with a Newey-West t-statistic of 6.67. This suggests that after controlling for the market, size, and book-to-market factors, the return difference between high liquidity shock and low liquidity shock deciles remains positive and significant. Alternatively stated, these well-known factors do not explain the positive relation between liquidity shocks and future stock returns.

Lastly, we investigate the source of this significant return difference between high liqiudity shock and low liquidity shock deciles: is it due to underperformance by stocks in the low liquidity shock decile, or outperformance by stocks in the high liquidity shock decile, or both? For this, we compare

[9] Following Newey and West (1987), we set the number of lags q to 5 using their formula: $q = floor\left(4 \times \left(\frac{T}{100}\right)^{\left(\frac{2}{9}\right)}\right)$, where $floor$ denotes the floor function, and T equals 569, corresponding to the 569 months between August 1963 to December 2010.

the performance of the low liquidity shock decile to the performance of the rest of deciles as well as the performance of rest of deciles to the performance of the high liquidity shock decile, both in terms of raw returns and risk-adjusted returns. Analyzing the rows starting with "High LIQU - Rest of Deciles" and "Low LIQU - Rest of Deciles" in Panel A of Table 2, we find that, on average, high LIQU stocks generate 0.42% more monthly raw returns compared to the rest of their peers (with a t-statistic of 3.64), and low LIQU stocks produce 0.94% less monthly raw returns compared to the rest of their peers (with a t-statistic of 7.16), suggesting that the positive and significant return difference between high LIQU and low LIQU stocks is due to both outperformance by high LIQU stocks and underperformance by low LIQU stocks. Finally, when the 3-factor alpha differences are considered, the outcome remains the same; stocks in the high LIQU decile generate significantly higher risk-adjusted returns compared to the rest of the crowd (0.59% 3-factor alpha difference with a t-statistic of 5.32), while stocks in the low LIQU decile produce significantly smaller risk-adjusted returns compared to the rest of the crowd (0.99% 3-factor alpha difference with a t-statistic of 6.95). In sum, all of these estimates confirm our earlier findings for the existence of a positive and significant relation between liquidity shocks and future stock returns.

The last column of Panel A of Table 2 reports the average market share of each LIQU portfolio. The market share decreases from the lowest to the highest LIQU deciles. Nonetheless, the lowest LIQU portfolio has an average market share of about 6%. This finding, together with the almost monotonic cross-sectional return patterns associated with liquidity shocks, suggests that the positive pricing effect is not solely driven by extremely small stocks that are economically insignificant.

To alleviate the concern that the CRSP decile breakpoints are distorted by the large number of small NASDAQ and Amex stocks, we reconstruct the LIQU portfolios based on the NYSE decile breakpoints (see Fama and French (1992)). In other words, the decile breakpoints of LIQU portfolios are first determined using the NYSE stocks only, and then all NYSE/AMEX/NASDAQ stocks are sorted into the 10 decile portfolios of LIQU. Panel B of Table 2 shows that the positive predictive power of liquidity shocks remain intact. The average raw return difference and the 3-factor alpha difference between high

LIQU and low LIQU deciles are 1.18% and 1.38% per month, respectively, and both are significant at the 1% level with the corresponding t-statistics of 5.86 and 6.83. Similar to our findings in Panel A of Table 2, the positive and significant return difference between stocks in the high LIQU and low LIQU deciles is due to both outperformance by high LIQU stocks and underperformance by low LIQU stocks.[10]

3.2. Bivariate portfolio-level analysis

As discussed earlier, liquidity shocks are highly correlated with many well-known characteristics that forecast cross-sectional stock returns. To get a clearer picture of the composition of the high and low liquidity shock portfolios, Table 3 presents summary statistics for the stocks in the deciles. Specifically, the table reports the average across the months in the sample of the average values within each month of various characteristics for the stocks in each decile. We report average values for liquidity shock (LIQU), log market capitalization (LNME), book-to-market ratio (BM), market beta (BETA), Amihud's illiquidity measure (ILLIQ), price per share (in dollars), return over the 11 months prior to portfolio formation (MOM), return in the portfolio formation month (REV), co-skewness (COSKEW), monthly idiosyncratic volatility (IVOL), maximum daily return in a month (MAX), and analyst dispersion (DISP).

As we move from the Low LIQU to the High LIQU decile, the average across months of the average liquidity shocks of stocks increases from -3.39 to 1.47 (as previously reported in Table 2, Panel A). Table 3 shows that stocks in the low LIQU decile are small, illiquid, and low-priced. The average book-to-market ratio of the stocks in the low LIQU decile is also high, indicating that there are more value stocks in the low LIQU decile, and more growth stocks in the high LIQU decile. Moreover, stocks in the low LIQU decile have higher idiosyncratic risk, higher market risk, higher disagreement among the analysts, lower coskewness, and are more lottery-like assets. Finally, stocks in the low LIQU

[10] Due to space constraints, the results are presented based on the CRSP breakpoints for the remainder of the paper.

decile have much lower past 1-month and 12-month returns (i.e., short-term and medium-term losers), whereas stocks in the high LIQU decile are short-term and medium-term winners.

Given these differing characteristics, there is some concern that the 3-factor model used in Table 2 to calculate alphas is not adequate to capture the true difference in risk and expected returns across the portfolios sorted on liquidity shock. Although the 3-factor model of Fama and French (1993) controls for differences in market beta, size, and book-to-market, it does not control explicitly for the differences in expected returns due to differences in illiquidity, past return characteristics (reversal, momentum), co-skewness, idiosyncratic volatility, analyst disagreement, and demand for lottery-like stocks. Hence, in the following three sections, we provide several specifications to control for these other factors.

In this section, we perform bivariate sorts on LIQU in combination with market beta (BETA), size (LNME), book-to-market ratio (LNBM), short-term reversal (REV), co-skewness (COSKEW), idiosyncratic volatility (IVOL), extreme positive daily return (MAX), and analyst dispersion (DISP). We show that each control alone fails to subsume the pricing effect of LIQU.

Panel A of Table 4 reports the results of conditional bivariate sorts. Stocks are first sorted into quintile portfolios based on one control variable, and then into LIQU quintiles within each control variable quintile. We then group together the stocks in the same liquidity shock quintiles and report the average quintile returns and the high-minus-low LIQU quintile return differences for the following month. We report the average returns of the LIQU portfolios, averaged across the five control quintiles to produce quintile portfolios with dispersion in LIQU but with similar levels of the control variable. The predictive power of LIQU remains intact in dependent bivariate portfolios. The average raw return differences, ranging from 0.63% to 1.26% per month, are all significant at the 1% level based on the Newey-West t-statistics. The corresponding 3-factor alphas are also significantly positive, ranging from 0.70% to 1.40% per month.

Panel B of Table 4 presents the same set of results from the independent bivariate sorts. For each month, we conduct two independent sorts of stocks into quintiles based on LIQU and a control variable at the beginning of the month. We then take the intersection of these sorts to form 25 portfolios. We hold these portfolios for one month and then rebalance at the end of the month. This sorting procedure creates a set of liquidity shock portfolios with nearly identical levels of the control variable. The independent sort results are very similar to those obtained from dependent sorts – the return differentials and the corresponding 3-factor alphas are positive and significant at the 1% level; the average raw return differences are in the range of 0.65% to 1.37% per month with the t-statistics ranging from 3.72 to 8.59. Similarly, the 3-factor alphas are in the range of 0.69% and 1.49% per month with the t-statistics ranging from 4.69 to 9.59.

3.3. firm level cross-sectional regressions

While portfolio-level analysis has an advantage of being nonparametric, it does not allow us to account for the possible simultaneous effect of the control variables. To check whether the predictive power of liquidity shocks remains strong after simultaneously controlling for the competing predictors of stock returns, we run monthly cross-sectional predictive regressions of the form:

$$R_{i,t+1} = \alpha_{t+1} + \gamma_{t+1} LIQU_{i,t} + \varphi_{t+1} X_{i,t} + \varepsilon_{i,t+1}, \tag{7}$$

where $R_{i,t+1}$ is the realized excess return on stock i in month $t+1$, $LIQU_{i,t}$ is the liquidity shock of stock i in month t, and $X_{i,t}$ is a vector of control variables for stock i in month t.

Table 5 presents the time-series averages of the slope coefficients from the firm level Fama and MacBeth (1973) cross-sectional regressions of one-month ahead stock returns on liquidity shocks (LIQU) and the control variables. Specifically, Model 1 serves as the baseline model, where the control variables are the market beta (BETA), the log market capitalization (LNME), and the log book-to-market ratio (BM). We then add each other control variable one at a time to avoid multicollinearity. Model 2 controls for the price momentum (MOM), Model 3 controls for the short-term return reversal (REV), Model 4 controls for the co-skewness (COSKEW), Model 5 controls for the idiosyncratic volatility

(IVOL), Model 6 controls for the maximum daily return in the previous month (MAX), and Model 7 controls for the dispersion of analyst forecasts (DISP). Models 8 through 12 are similar to Models 3 through 7, with price momentum variable included additionally.

The average slopes and the corresponding Newey-West t-statistics reported in Table 5 provide standard Fama and MacBeth (1973) tests for determining which explanatory variables on average have non-zero premia. Across all the specifications in Table 5, the average slope coefficients of LIQU are positive, ranging from 0.16 and 0.29, and highly significant with the t-statistics ranging from 5.52 to 12.88. The economic significance of the average slope coefficients of LIQU can be interpreted based on the long-short equity portfolios. As reported in Table 2 (Panel A), the difference in LIQU values between average stocks in the high and low LIQU deciles is 4.86. Hence, the average slopes of 0.16 and 0.29 imply that a portfolio short-selling stocks with the largest decrease in liquidity (stocks in Decile 1) and buying stocks with the largest increase in liquidity (stocks in Decile 10) will generate a return in the following month by between 0.78% and 1.41%, controlling for everything else. This return magnitude is in line with the univariate and bivariate portfolio results.

The average slopes on the control variables are in line with the earlier studies. Specifically, the firm size, idiosyncratic volatility, extreme daily return in a month, short-term reversal, and analyst dispersion are significantly negative predictors of future stock returns over our sample period, whereas momentum and book-to-market are reliably positive predictors of future returns. The market beta and coskewness are not significant in any of the specifications, results consistent with Fama and French (1992), Ang, Hodrick, Xing, and Zhang (2006), and follow-up studies.

3.4. Controlling for illiquidity-related variables

Table 1, Panel B shows that our liquidity shock variable is correlated with other liquidity related variables (i.e., the level of liquidity, the sensitivity to systematic liquidity, and the volatility of liquidity) that may also affect stock returns. Therefore, it is important to examine whether the strong relationship between liquidity shocks and future returns is driven by its association with these other liquidity variables.

In this section, we perform bivariate portfolio analysis and multivariate Fama-MacBeth regressions that control for the liquidity-based variables. We use Amihud's (2002) illiquidity (ILLIQ) to control for the level of illiquidity, and Pastor and Stambaugh's (2003) liquidity beta to proxy for sensitivity to innovation in market-wide liquidity. Following Chordia, Subrahmanyam, and Anshuman (2001) and Akbas, Armstrong, and Petkova (2010), we use the standard deviation of ILLIQ of monthly turnover (SDTURN), and the coefficient of variation in the Amihud's illiquidity (CVILLIQ). In addition, we control for the mean (MILLIQ) and volatility (SDILLIQ) of Amihud illiquidity over the past 12 months to capture the amount of risk associated with liquidity variations.

Panel A of Table 6 reports the results of conditional (dependent) bivariate sorts where individual stocks are first sorted by the liquidity-related control variables and then by the liquidity shock variable. After controlling for alternative measures of liquidity and liquidity risk, the average raw return differences between high LIQU and low LIQU quintiles are in the range of 0.95% and 1.12% per month and highly significant with the t-statistics ranging from 5.69 to 7.25. Similarly, the 3-factor alphas are positive, ranging from 1.11% to 1.18%, and highly significant with the t-statistics ranging from 6.59 to 7.60. This result suggests that, even after accounting for other liquidity related variables that are known to predict expected returns, portfolios long stocks in the quintile with the largest increase in liquidity and short stocks in the quintile with the largest decrease in liquidity leads to a risk-adjusted return of more than 1% per month.

Panel B of Table 6 reports the results of multivariate Fama-MacBeth regressions that control for market beta, size, book-to-market ratio, momentum, and the liquidity-based control variables one at a time. The average slope coefficients of liquidity shock are highly significant and positive, ranging from 0.18 and 0.24. These numbers can be interpreted similarly. Given the difference between the average liquidity shocks for stocks in the highest and lowest liquidity-shock deciles of 4.86, a long-short portfolio based on liquidity shocks can generate an average monthly alpha of between 0.92% and 1.17%.

Hence, our results suggest that the magnitude of liquidity shocks is not only statistically significant, but also has an economically important effect on future returns that is beyond what's captured by the other liquidity related variables.

Regarding the average slope coefficients of the liquidity-related control variables, consistent with the findings documented in earlier studies, ILLIQ, PS, as well as MILLIQ are significantly positive predictors of future returns over our sample period. In terms of the volatility of liquidity, the coefficients of SDILLIQ and CVILLIQ are significantly positive, while SDTURN is significantly negative. Overall, the results in Table 6 indicate that controlling for a large set of liquidity and liquidity risk variables does not impact the significantly positive link between liquidity shocks and future stock returns.

4. Investigating the Underlying Cause of the Puzzle

Our finding of the positive cross-sectional link between firm level liquidity shocks and future stock returns seems to be puzzling given that liquidity shocks are persistent and that the level of illiquidity has found to be positively priced in the cross-section of expected returns. It seems logical that shocks that decrease liquidity this period will lead to higher levels of illiquidity in the future. Therefore, when the market immediately reacts to shocks and to the full extent, negative liquidity shocks should lead to a higher risk premium and thus an instantaneous price decrease (lower contemporaneous return) and higher future returns.

To determine why there is instead a positive relation between liquidity shocks and future returns, we explore an alternative hypothesis: when the market underreacts to the liquidity shocks, the full effect of liquidity shocks is reflected in prices gradually over time, resulting in a continuation of negative returns in the near future.

To examine the underreaction hypothesis, we study the effect of liquidity shocks on stock returns both immediately and over time. Table 7 documents the contemporaneous relationship between liquidity shocks and stock returns. Panel A examines the same-month returns on portfolios sorted by innovations in liquidity (LIQU). It shows a monotonic positive relationship between liquidity shocks and returns: the decile portfolio with the greatest liquidity shocks experiences a contemporaneous return of 2.57%, while the decile with the lowest liquidity shocks experiences a contemporaneous return of -5.62%. The Fama-MacBeth regression results shown in Panel B confirms that this positive contemporaneous relationship is not driven by other forces such as the level of liquidity or other systematic risk factors and firm characteristics. Hence, this initial reaction of liquidity shocks is consistent with the argument put forth in the prior literature: a negative and persistent liquidity shock increases future expected illiquidity and therefore should lead to an immediate decrease in the stock price due to a higher liquidity risk premium.

We then ask whether the effect of liquidity shocks have been fully reflected in contemporaneous stock prices by examining future returns of various holding periods. We estimate predictive regressions of monthly stock returns over month $t+1$ to $t+60$ against liquidity shock (LIQU) in month t using the Fama and MacBeth (1973) methodology. Figure 4 depicts the average slope coefficients of LIQU. The dashed lines define the 95% confidence bounds, calculated based on the Newey and West (1987) standard errors. The results show that the negative liquidity shocks continue to drive negative returns up to 6 months after the shock. This evidence suggests that there exists considerable underreaction to firm level liquidity shocks and the underreaction can last for a substantial amount of time. The horizon of underreaction documented here is consistent with the pattern established by other empirical papers. Bernard and Thomas (1989) find that underreaction to earnings announcements can last for up to a quarter, until the next earnings announcement. Hong, Lim, and Stein (2000) find that slow information diffusion can lead to stock market underreactions, which results in return predictability for 10 months or even longer (especially for stocks with low analyst coverage). Hirshleifer, Lim, and Teoh (2009) show that the underreaction to earnings news distracted by other information events can be significant in the 60-day cumulative returns after the announcement.

We explore two possible causes of stock market underreaction to liquidity shocks: limited investor attention and illiquidity. One mechanism proposed in the literature to explain underreaction to information is investor attention (See, for example, Huberman and Regev (2001), Hirshleifer and Teoh (2003), Hirshleifer, Hou, Teoh, and Zhang (2004), Hou and Moskowitz (2005), Peng (2005), Gabaix, Laibson, Moloche, and Weinberg (2006), Peng and Xiong (2006), Hirshleifer, Lim, and Teoh (2009), Hong, Torous, and Valkanov (2007), DellaVigna and Pollet (2007, 2009), Barber and Odean (2008), Cohen and Frazzini (2008), Hirshleifer, Lim, and Teoh (2011), and Hirshleifer, Hsu, and Li (2012)).

A large body of psychological research shows that there is a limit to the central cognitive-processing capacity of the human brain.[11] The limited availability of time and cognitive resources imposes constraints on how fast investors can process information. The less attention investors pay to a stock, the slower such information can be incorporated into its prices, and the more delayed the reaction to information.

Compared to the types of information studied in the aforementioned literature (earnings news, demographic information, new products, returns of related firms, etc.), liquidity shocks are less well defined and its pricing implications are harder to interpret by average investors, and as a result, investors are more likely to ignore this "news". In this case, when firm level liquidity decreases, the effect of increased risk premium and lower stock prices is not immediately incorporated fully by the stock market, rather, the negative price impact spills over to the future months. The attention-based underreaction hypothesis further predicts that the return predictability of liquidity shocks should be stronger for stocks in which investors pay less attention.

Illiquidity may also result in delays in price adjustments: if information is revealed through trading, then for illiquid stocks, since it is much harder to trade, information is revealed more slowly. This mechanism makes sense especially for private information. The only way for these types of information to be incorporated into prices is through trading, and the informed traders trade less aggressively when liquidity is low or when transaction costs are high. The mechanism is less obvious for public information such as publicly observable changes in liquidity (especially given that our liquidity shocks are simple to compute). In a market in which participants such as market makers and traders immediately

[11] See Pashler and Johnston (1998) for a review of these studies.

react to public information, prices can be updated right away without any trading. However, if market participants are heterogeneous in processing information, together with limits to arbitrage, illiquidity may still lead to slow price adjustment following public information arrival. Hence, it is plausible that illiquidity can hamper price discovery, which leads to slow price adjustment following liquidity shocks. The illiquidity-based underreaction hypothesis predicts that the positive return predictability of liquidity shocks should be stronger for less liquid stocks.

To empirically test the attention-based underreaction hypothesis, we form subsamples that vary by the degree of investor attention and compare the relation between liquidity shocks and subsequent returns in these subsamples.

Following Hirshleifer and Teoh (2003), Peng (2005), and Hirshleifer, Hsu, and Li (2012), we adopt firm size and analyst coverage as proxies for investor attention. Smaller firms and firms with lower analyst coverage receive less attention from investors. As a result, we expect these firms to exhibit more delayed reaction to information contained in liquidity shocks, and thus liquidity shocks can generate greater return predictability. Small firms and firms with lower analyst coverage have slower information diffusions are also consistent with evidence found in price momentum effect (Hong, Lim, and Stein (2000)), stock return lead-lags (Brennan, Jegadeesh, and Swaminathan (1993); Hong, Torous, and Valkanov (2007); Hou (2007); Cohen and Frazzini (2008)), post earnings announcement drifts (Chambers and Penman, 1984; Bernard and Thomas, 1989), and the accrual anomaly (Mashruwala, Rajgopal, and Shevlin (2006)). In addition, since institutional investors are more likely to pay more attention to individual stocks than retail investors due to their expertise and economies of scale in gathering information, stocks with more institutional ownership tend to receive more investor attention. Thus, we use institutional ownership as our third attention proxy, with the caveat that institutional ownership may also capture the relaxation of short sell constraints.

We use firm size (LNME), analyst coverage (CVRG), and institutional holdings (INST) to proxy for investor attention. We expect that small stocks, stocks with low analyst coverage and low institutional ownerships are more likely to underreact to liquidity shocks and thus there should be a stronger positive relation between liquidity shocks and future returns.

We first sort stocks into quintile portfolios based on an attention proxy, and then within each proxy quintile into liquidity shock quintile portfolios. We follow the prior literature and use NYSE breakpoints.[12] Table 8 reports the details of bivariate sorts. The results are consistent with the attention-based underreaction hypothesis. A portfolio long stocks with positive liquidity shocks (increase in liquidity) and short stocks with negative liquidity shocks (decreases in liquidity) leads to a monthly return of 143 basis points for stocks in the smallest size quintile and a return of only 40 basis points for stocks in the largest size quintile. While the long-short portfolio generates a large and significant raw return for the lowest analyst coverage and the lowest institutional holding quintiles (raw returns are 138 and 160 basis points, respectively), the return is no longer significant in the highest analyst coverage and the highest institutional holdings quintiles (raw returns are 23 and 35 basis points, respectively). These results suggest that, underreaction to liquidity shocks is stronger and more significant for stocks that receive less investor attention: small, less-covered stocks, and stocks minimally held by institutional investors.[13]

To test whether illiquidity-driven slow price adjustment can also contribute to market underreaction to liquidity shocks, we analyze how the degree of underreaction is related to the level of the stock's illiquidity. We first sort stocks into quintiles every month based on the Amihud's illiquidity measure (ILLIQ), and then within each ILLIQ quintile into quintiles on liquidity shocks (LIQU). To facilitate comparison to the results based on the attention hypothesis, we use the NYSE breakpoints for both ILLIQ and LIQU quintiles.[14] Table 9 reports the equal-weighted average returns for each of the 5×5 portfolios of ILLIQ and ILIQU, the return difference (High$-$Low) between the highest and the lowest LIQU quintiles within each ILLIQ quintile, and the 3-factor alpha. The return differences and 3-factor alphas remain significantly negative across all ILLIQ quintiles. Moving from the lowest to the highest

[12]Our results remain similar if the size quintiles are formed based on the CRSP breakpoints.
[13]Intuitional ownership can also be a proxy for the relaxation of short-sell constraints.
[14]Our results remain similar when the CRSP counterparts are used.

ILLIQ quintile, the return difference between Quintile 5 and Quintile 1 LIQU portfolios increases from 48 to 150 basis points per month, and the corresponding 3-factor alpha increases from 53 to 152 basis points per month. These results are consistent with the illiquidity-based underreaction hypothesis that the market underreaction to liquidity shocks is stronger for less liquid stocks.

Our evidence is thus consistent with both the attention- and the illiquidity-based underreaction hypotheses. One might argue that the attention proxies we employ (size, analyst coverage, and institutional ownership) are highly correlated with the liquidity of a stock: Table 1, Panel B shows that the average correlations between illiquidity (ILLIQ) and firm size (LNME), analyst coverage (CVRG), and institutional ownership (INST) are -0.460, -0.243 and -0.296, respectively. So what the attention measures capture can actually be the effect of illiquidity, and vice versa. To disentangle the effect of investor attention from illiquidity and gauge the relative importance of the two mechanisms in contributing to markets' underreaction to liquidity shocks, we perform triple sorts as well as include both underreaction proxies and illiquidity as interaction variables with LIQU in Fama-MacBeth regressions.

We first examine whether, after controlling for illiquidity, investor attention can still affect market's underreaction to liquidity shocks. We sort stocks into quintiles on the Amihud's illiquidity measure (ILLIQ), stocks within each ILLIQ quintile are then sorted into quintiles on one of the three attention proxies – LNME, CVRG, and INST. Stocks within each of the 25 ILLIQ and attention variable groupings are further sorted into quintiles on liquidity shock (LIQU) using NYSE breakpoints. Table 10 reports the equal-weighted average returns for each of the 5×5 portfolios of the investor attention variable and LIQU, the return difference (High$-$Low) between the highest and lowest LIQU quintiles within each attention variable quintile, and the 3-factor alpha. After controlling for the level of illiquidity, a portfolio long stocks with positive liquidity shocks (increase in liquidity) and short stocks with negative liquidity shocks (decreases in liquidity) leads to a monthly return of 118 basis points for stocks in the smallest size quintile and a return of only 56 basis points for stocks in the largest size quintile, with a return differential of 62 basis points. Compared to the return differential of 103 basis points in Panel A of Table 8, it suggests that, 60% of the effect of firm size on underreaction is not related to stocks illiquidity. The corresponding 3-factor alphas display a very similar pattern as well. Similarly, the High$-$Low return differential across different analyst coverage (institutional ownership) groups is 69 basis points (80 basis points) per month. When compared to the return differential of 115 basis points (123 basis points) in Table 8, Panel B (Panel C), it suggests that 60% (65%) of the explanatory power of analyst coverage (institutional ownership) on underreaction is not due to illiquidity.

Next, we examine whether, after controlling for investor attention proxies, firm level illiquidity can still contribute to underreaction. We sort stocks into quintiles on one of the three attention proxies, stocks within each attention variable quintile are then sorted into quintiles on the Amihud's illiquidity measure (ILLIQ). Stocks within each of the 25 attention variable and ILLIQ groupings are further sorted into quintiles on liquidity shock (LIQU) using NYSE breakpoints. Table 11 reports the equal-weighted average returns for each of the 5×5 portfolios of the ILLIQ and LIQU, the return difference (High$-$Low) between the highest and lowest LIQU quintiles within each ILLIQ variable quintile, and the 3-factor alpha. After controlling for firm size, a portfolio long stocks with positive liquidity shocks and short stocks with negative liquidity shocks has a monthly return of 126 basis points for the most illiquid stocks and a return of 87 basis points for the most liquid stocks, with a marginally significant return differential of 39 basis points. Compared to the return differential of 102 basis points in Table 9, it suggests that, even after controlling for firm size, illiquidity still contributes 38% of the cross-sectional differences in underreaction. The High$-$Low return differentials across different illiquidity groups are much larger when analyst coverage and institutional ownership are controlled for: the differentials are 91 and 96 basis points, respectively. It suggests that 89% (94%) of the explanatory power of illiquidity on underreaction is not due to analyst coverage (institutional ownership).

In addition to triple sorts, we investigate the relative importance of the attention- and the illiquidity-based mechanisms of underreaction using Fama-MacBeth regressions. For each month, one-month ahead excess returns (Panel A) or 6-month cumulative excess returns (Panel B) are regressed against the liquidity shock (LIQU), the level measure (ILLIQ), the interaction between ILLIQ and LIQU (ILLIQ $\times$ LIQU), one attention proxy, and its interaction with LIQU, along with a large set of cross-sectional controls: the market beta (BETA), the natural logarithm of the book-to-market equity ratio (LNBM), the momentum return (MOM), the short-term reversal (REV), the co-skewness (COSKEW), the idiosyncratic volatility (IVOL), the maximum daily return in a month (MAX), the analyst earnings forecast dispersion (DISP), the Pastor and Stambaugh liquidity beta (PS), the standard deviation of TURN (SDTURN), and the coefficient of variation in the Amihud's illiquidity measure (CVILLIQ). Table 12 reports the average coefficients of LIQU and the interactions between the attention variable and LIQU and between ILLIQ and LIQU.[15] Model 1 is the baseline model without any interaction variables. Model 2 introduces the interaction of attention proxy with liquidity shocks (Attention $\times$ LIQU), model 3 introduces the interaction of illiquidity levels with liquidity shocks (ILLIQ $\times$ LIQU), and model 4 includes the above two interaction variables simultaneously.

In Panel A, Attention $\times$ LIQU is negative and significant for both models 2 and 4, across all three attention proxies, suggesting that the return predictability of liquidity shocks is stronger for low attention stocks, even after controlling for any potential effect of illiquidity levels. ILLIQ $\times$ LIQU is not significant by itself in model 3, but becomes positive and statistically significant in model 4 when the attention interaction variable is also included (analyst coverage or institutional ownership are used as attention proxies). This suggests that illiquidity-driven slow price adjustment may also be a contributing factor to markets' underreaction to liquidity shocks. Furthermore, the different level of significance of the attention interaction variable and the illiquidity interaction variable in model 2 versus model 3 suggests that these two interaction variables are not capturing the same effect, and that both the attention- and the illiquidity-based mechanisms contribute to the market's underreaction to liquidity shocks.

Panel B shows that liquidity shocks (LIQU) are still significant in predicting future six-month cumulative returns. More importantly, the attention interaction variables are significant across all three attention measures, while the illiquidity interaction variable is only significant when the interaction of institutional ownership with LIQU is included. This indicates that the attention- and the illiquidity-

[15]We suppress the coefficient estimates of the cross-sectional controls. They are available upon request.

based mechanisms may operate at different horizons – while both are significant for short term return continuations, the attention-based mechanism may be more important for longer-run underreactions.

To summarize, we find that the positive relationship between liquidity shocks and future returns are due to markets' underreaction to liquidity shocks. Our evidence further suggests that both investor inattention and illiquidity contribute to this underreaction and that these two mechanisms are considerably different from each other.

5. Robustness

In this section, we run a battery of robustness checks for our main findings. We show that our results are robust to (*i*) alternative measures of liquidity shocks; (*ii*) screening for stock price, stock exchange, and listing status; (*iii*) different portfolio weighting schemes; (*iv*) subsample analysis including expansionary and recessionary periods; and (*v*) an alternative measure of illiquidity beta.

5.1. A conditional measure of liquidity shocks

In this section, we propose a more sophisticated parametric methodology to define a conditional measure of liquidity shocks. For stock i, we estimate the conditional mean and conditional volatility of illiquidity jointly:

$$ILLIQ_{i,t} = \alpha_{0,i} + \alpha_{1,i} ILLIQ_{i,t-1} + \alpha_{2,i}\varepsilon_{i,t-1} + \varepsilon_{i,t} = \mu_{i,t} + \sigma_{i,t} z_{i,t}, \tag{8}$$

$$\sigma^2_{i,t} = \beta_{0,i} + \beta_{1,i}\sigma^2_{i,t-1} + \beta_{2,i}\sigma^2_{i,t-1} z^2_{i,t-1}, \tag{9}$$

$$z_{i,t} \equiv \frac{\varepsilon_{i,t}}{\sigma_{i,t}}, \tag{10}$$

where $\mu_{i,t}$ and $\sigma_{i,t}$ are, respectively, the conditional mean and conditional volatility of illiquidity that are assumed to follow an ARMA(1,1) and GARCH(1,1) process (see Engle (1982) and Bollerslev (1986));

$z_{i,t}$ is the standardized innovation in illiquidity, and assumed to have the standard normal distribution.[16] We define the conditional liquidity shock, denoted LIQCU, as the negative of $z_{i,t}$. The parameters are estimated simultaneously by maximizing the following conditional log-likelihood function based a 60-month rolling sample that requires a minimum of 24 observations and is updated on a monthly basis:

$$\mathcal{L} = \sum_{t=1}^{T} ln\left(f\left(z_{i,t}|\alpha_{0,i},\alpha_{1,i},\alpha_{2,i},\beta_{0,i},\beta_{1,i},\beta_{2,i}\right)\right). \tag{11}$$

The time-series averages of the cross-sectional mean of the estimated parameters $\widehat{\alpha_{0,i}}$, $\widehat{\alpha_{1,i}}$, $\widehat{\alpha_{2,i}}$, $\widehat{\beta_{0,i}}$, $\widehat{\beta_{1,i}}$, and $\widehat{\beta_{2,i}}$ are 0.46, 0.72, -0.31, 1.14, 0.61, and 0.24, respectively. These results confirm that the conditional mean of illiquidity is highly persistent, and the volatility of illiquidity is time-varying. Moreover, these parameter estimates imply a long-run average level (unconditional mean) of illiquidity of 2.14, and the unconditional illiquidity volatility of 2.76, which are very much in line with their nonparametric counterparts reported in Panel A of Table 1.[17]

The bottom panel of Figure 3 displays the equal-weighted average of the firm level conditional measures of liquidity shocks (LIQCU) obtained from equations (8)-(10). Similar to our findings for the nonparametric measure of liquidity shock, the bottom panel of Figure 3 presents cyclical decreases in liquidity shocks during periods corresponding to the economic recessions, stock market downturns, and major political upheavals. Since the month-to-month variations in the conditional mean and conditional volatility are well captured by the ARMA-GARCH process, the conditional measure of liquidity shocks (LIQCU) provides a strong time-series variation. Moreover, the empirical distribution of LIQCU is closer to a normal distribution with much fewer outliers compared to the distribution of LIQU. Specifically, the median conditional liquidity shock is 0.36 over our sample period and the mean

[16]At an earlier stage of the study, we used the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) to determine the optimal lag length for ARMA-GARCH specification. Since the improvement in terms of AIC and SBC is not high when we use larger number of lags, we decided to use the most parsimonious model in equations (8) and (9). Moreover, the qualitative results from alternative specifications of the ARMA-GARCH model turned out to be similar to those reported in Table 13.

[17]Panel A of Table 1 shows that the time-series average of the cross-sectional mean of the Amihud's illiquidity measure (ILLIQ) is 2.33. Hence, the set of parameters that govern the dynamics of the conditional mean of illiquidity implies that the long-run average level (unconditional mean) of illiquidity is $0.46 + 0.72 \times 2.33 = 2.14$. The unconditional volatility of illiquidity is calculated as $\left(\frac{\beta_0}{1-\beta_1-\beta_2}\right)^{1/2} = 2.76$.

LIQCU is 0.14. The average skewness and kurtosis of conditional liquidity shocks are -0.93 and 1.25, respectively, indicating that on average there are fewer outliers in the tails of the LIQCU distribution.

Panel A of Table 13 reports the correlation coefficients between the conditional liquidity shock obtained from the ARMA(1,1)-GARCH(1,1) parametric method and the other liquidity-based variables. The correlations of LIQCU with the conditional mean and volatility of illiquidity are negligible. On the other hand, LIQCU is highly correlated with the nonparametric liquidity shock measure (LIQU), and negative spread changes (SPRDU) obtained from the nonparametric method with average correlation coefficients of 0.70 and 0.32, respectively.

We perform univariate portfolio analysis and run the Fama-MacBeth regressions to examine whether the positive predictive power of liquidity shocks remains robust to this conditional measure. Panel B of Table 13 shows that the return differential and the 3-factor alphas are 0.73% and 0.79% per month, respectively, and they are significant at the 1% level. The average market shares across different decile portfolios are somewhat more balanced than those based on the nonparametric liquidity shock.

Panel C of Table 13 reports the average coefficient estimates from the Fama-MacBeth regressions. The average slope coefficients of LIQCU range from 0.14 to 0.30 and are significant at the 1% level. These numbers imply that an increase in liquidity shock of 3.15 (corresponding to the difference between the average liquidity shocks for stocks in the highest and lowest LIQCU deciles) will raise the return in the following month by between 0.44% and 0.95%. These results are in line with those based on the nonparametric liquidity shock.

Consistent with the findings from the original nonparametric measure of liquidity shock (LIQU), the significant return difference between high LIQCU and low LIQCU stocks is due to both outperformance by high LIQCU stocks and underperformance by low LIQCU stocks. On average, high LIQCU stocks generate 0.23% more monthly raw returns compared to the rest of their peers (with a t-statistic of 3.67), and low LIQCU stocks produce 0.59% less monthly raw returns compared to the rest of their peers (with a t-statistic of 6.29). Finally, when the 3-factor alpha differences are considered, the outcome remains the same; stocks in the high LIQCU decile generate significantly higher risk-adjusted returns compared to the rest of the crowd (0.24% 3-factor alpha difference with a t-statistic of 3.79), while stocks in the low LIQCU decile produce significantly smaller risk-adjusted returns compared to the rest of the crowd (0.63% 3-factor alpha difference with a t-statistic of 6.77).

5.2. Liquidity shock based on changes in bid-ask spreads

We adopt an alternative measure of liquidity based on the quoted bid-ask spread (SPRD). We construct the firm's negative spread shocks (SPRDU) as:

$$SPRDU_{i,t} = -\frac{SPRD_{i,t} - AVGSPRD_{i|t-12,t-1}}{SDSPRD_{i|t-12,t-1}}, \tag{12}$$

where $AVGSPRD_{i|t-12,t-1}$ and $SDSPRD_{i|t-12,t-1}$ are the average and standard deviation of $SPRD_i$ over the past 12 months.

Panel A of Appendix Table A1 shows that the return differential and the 3-factor alphas for the SPRDU sorted portfolios are 0.71% and 1.02% per month, respectively, and they are significant at the 5% level or better. Panel B of Appendix Table A1 reports the coefficient estimates from the Fama-MacBeth regressions. The average slope coefficients of SPRDU range from 0.09 and 0.29, with Newey-West t-statistics in the range of 2.09 to 8.43. The average coefficients of SPRDU, in conjunction with the SPRDU differential between the highest and lowest SPRDU deciles, 4.50 (reported in Appendix Table A1, Panel A), imply that a portfolio buying stocks of the highest SPRDU decile and short-selling stocks of the lowest SPRDU decile, on average, yields monthly return in the range of 0.41% and 1.31% in the following month, after controlling for other cross-sectional predictors.

Overall, our results are robust to modeling liquidity shocks based on the parametric and nonparametric methods, and to alternative liquidity measures.

5.3. Screen on price, listing status, stock exchange, and liquidity shock

In this section, we show that our finding is not driven by penny stocks, the inclusion of NASDAQ stocks, delisted stocks whose liquidity decreases substantially prior to delisting, resulting in lower future stock returns, or stocks in the lowest LIQU decile of the original sample.

We apply five layers of screens: (*i*) eliminate stocks with price less than $5 per share; (*ii*) limit to stocks that are active with the delisting code on the CRSP database set to either 100 or missing; (*iii*) limit to NYSE-traded stocks; (*iv*) stocks listed on the NYSE with price no less than $5 per share; and (*v*) eliminate stocks that fall into the lowest LIQU decile of the original sample. Appendix Table A2 reports the results of the univariate portfolio sorts based on the five screened samples. The results show that the predictive ability of liquidity shocks remains intact. The return differentials and the 3-factor alphas are positive and highly significant, ranging from 0.69% to 1.11% per month, and from 0.88% and 1.28% per month, respectively.

5.4. Portfolio weighting schemes

We have so far presented evidence of equal-weighted portfolio returns and show that our results are not driven by small, illiquid, and low-priced stocks. We now examine this issue using alternative weighting schemes in portfolio formation and investigate whether the significantly positive link between liquidity shocks and future stock returns remains intact if stocks are sorted into the value-weighted, price-weighted, and liquidity-weighted portfolios, which give relatively more weights to bigger stocks, higher-priced stocks, and more liquid stocks, respectively.

Appendix Table A3 shows that the predictive power of liquidity shocks is robust across different weighting schemes. As presented in the first two columns, the average raw return difference between the value-weighted high and low LIQU portfolios is about 0.55% per month with the Newey-West t-statistic of 3.44, and the corresponding 3-factor alpha is also positive, 0.76% per month, and highly significant with a t-statistic of 4.16. Somewhat stronger results are obtained for the price-weighted portfolios; the average return and alphas differences between the price-weighted high and low LIQU portfolios are 0.89% and 1.08% per month, respectively, and highly significant with the t-statistics larger than five in absolute value. As shown in the last two columns of Appendix Table A3, similar strong results are obtained for the liquidity-weighted portfolios.

5.5. Recessionary vs. expansionary periods

In this section, we examine whether our findings are sensitive to the state of the economy. We first show that our finding is not solely driven by the most recent financial crisis period, July 2007 to June 2009. The first two columns of Appendix Table A4 show that, excluding the most recent financial crisis period, the long-short equity portfolio sorted on liquidity shocks generates a return that is almost identical to the full sample results presented in Table 2. The next four columns present results for NBER expansion and recession periods, respectively. Again, the sub-period analysis produces results that are very similar to those using the full sample, suggesting that our results are robust to different states of the economy.

5.6. Subsample analysis

We have shown that our main findings are not driven by recessionary, expansionary, or recent financial crisis periods. In this section, we provide a thorough subsample analysis by dividing our full sample into five decades: August 1963-July 1973, August 1973-July 1983, August 1983-July 1993, August 1993-July 2003, and August 2003-December 2010.

Appendix Table A5 shows that the average return differences between the High and Low LIQU portfolios are negative and highly significant for all decades, except for the last, shorter subsample. The 3-factor alpha differences between the extreme portfolios of LIQU are positive and highly significant for all decades, without any exception. Specifically, the average raw return differences are, respectively, 1.27%, 0.75%, 1.49%, 1.83%, and 0.65% per month for the aforementioned decades, and they are highly significant, except for the last subsample (August 2003-December 2010); the return spread is economically significant, 0.65% per month, but it is statistically weak because of the smaller number of observations. The corresponding alpha differences are economically larger, 1.35%, 1.05%, 1.49%, 2.03%, and 0.98% per month, and they are all statistically significant as well. These results show that the strong positive link between liquidity shocks and future returns are robust across different sample periods.

5.7. An alternative measure of exposure to market-wide illiquidity

In the previous sections, we show that our findings are robust to controlling for the Pastor and Stambaugh (2003) measure of firms' exposures to systematic liquidity shocks. We now construct an alternative systematic liquidity shock variable that is based on our main illiquidity measure, the Amihud's (2002) illiquidity measure, and test whether firms' exposure to this alternative market-wide illiquidity variable can drive the cross-sectional return pattern that we found.

We extend the CAPM by introducing the aggregate market illiquidity factor:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \gamma_i ILLIQ_{m,t} + \varepsilon_{i,t}, \tag{13}$$

where $ILLIQ_{m,t}$ is the market-wide illiquidity proxied by the Amihud's (2002) illiquidity measure, defined as the cross-sectional average monthly illiquidity of all stocks in CRSP. Once we estimate the market beta (β_i) and the market illiquidity beta (γ_i) using observations over past 60 months (or a minimum of 24 observations as available), we examine whether stocks with higher market illiquidity beta (γ_i) generate higher returns next period. Our results from the firm level Fama-MacBeth regressions provide no evidence for a significant link between this measure of market illiquidity beta and future stock returns.[18] Therefore, this alternative measure of market liquidity exposure can not explain our results.

[18]This result remains intact with and without the control variables in the Fama-MacBeth regressions, which are available upon request.

6. Discussion of Alternative Mechanisms

We have shown that the effect of firm level liquidity shocks on stock returns are robust after controlling for various risk factors, including, especially, the level of illiquidity and the exposure to systematic liquidity risk. In this section, we discuss whether our findings can be explained by several other alternative mechanisms: flight to liquidity, overreaction, and liquidity timing.

One might argue that a liquidity shock can lead to a "flight to liquidity", i.e., investors rush to dump their illiquid stocks and shift their funds into the liquid ones. In this case, the assets with a negative liquidity shock can be oversold and we should expect their prices to come back in the future. This story can not explain why, on the contrary, we find that the prices of those that experienced a negative liquidity shock continue to go down for an extended period of time in the future. Furthermore, "flight to liquidity" usually occurs during a systematic market-wide liquidity crisis, while our findings are strong and robust for all periods including busts and booms. Hence, our results cannot be explained by "flight to liquidity", although the evidence of return continuation after a liquidity shock do lend support to investors' motive to dump their less liquid assets and move to more liquid assets.

Some may argue that the story can go the other way: in a liquidity crisis, rather than flight to liquidity, investors may choose to sell off liquid assets to meet margin constraints or capital requirements and hold on to illiquid assets as they can only be sold at fire sale prices. As a result, stocks that are subject to a positive liquidity shock (increases in liquidity) are oversold, and future returns should be positive as they rebound. On the other hand, stocks that are subject to a negative liquidity shock (decreases in liquidity) are not sold enough, and future returns should be negative as the prices of these assets come down later. This story can produce a positive relationship between liquidity shocks and future stock returns during crisis periods. However, it is not clear whether the effect should be there during normal periods. Given that our finding of a positive relationship between liquidity shocks and future stock returns are equally strong for non-crisis periods as well as recessionary and expansionary periods, it seems that the proposed story cannot fully explain our findings.

Instead of underreaction to liquidity shocks, can market overreact to liquidity shocks and would this overreaction drive our results? When market overreacts to liquidity shocks, for example, the immediate reaction to a negative liquidity shock is an excessively low stock price, followed by a continuation of positive return in the future as overreaction is eventually corrected in the long run. Thus, overreaction predicts a negative relationship between liquidity shocks and future returns, which is inconsistent with the positive relation we find instead.

Can the positive relationship between liquidity shocks and future returns be driven by positively autocorrelated liquidity shocks? That is, when negative liquidity shocks are followed by negative liquidity shocks in the future, would this lead to lower future returns? The answer is no if the market is efficient. If the market rationally and immediately reacts to liquidity shocks, it should have anticipated the correlated nature of the shock and should have factored it into prices, leaving no return predictability. Thus even positively correlated liquidity shocks should not be able to predict positive future returns.

Since a stock's liquidity and trading volume is highly related, we also examine whether the pricing effect of liquidity shocks is driven by the high volume return premium documented by Gervais, Kaniel, and Mingelgrin (2001). Following Gervais, Kaniel, and Mingelgrin (2001), stocks are first sorted into low, normal, and high volume portfolios based on the dollar trading volume (VOLD) on the last but second trading day in the portfolio formation month relative to daily dollar trading volume over the prior 49 trading days; stocks within each VOLD grouping are further sorted into quintiles based on liquidity shock (LIQU). Table 14 reports the equal-weighted average returns for each of the 3×5 portfolios of the VOLD and LIQU, the return difference (High$-$Low) between the highest and lowest LIQU quintiles within each VOLD grouping, and the 3-factor alpha. After controlling for VOLD, the return differences between the highest and the lowest LIQU quintiles within each VOLD portfolio range from 95 to 105 basis points per month, and significant at the 1% level. The 3-factor alphas are also highly significant, ranging from 110 to 119 basis points per month. The average return difference between the highest and the lowest LIQU quintiles by averaging returns across the three VOLD groupings and the corresponding 3-factor alpha are, respectively, 100 and 115 basis points per month, and significant at the 1% level. These results confirm that the return predictability of liquidity shocks are not due to the high volume return premium effect.

What generates firm level liquidity shocks? Can the return predictability of liquidity shocks really be capturing the effect of something else such as changes in expected future cash flows or changes in risk? In general, there could be many potential reasons that may generate firm level liquidity increases/decreases. Liquidity changes can be triggered by information releases such as earnings announcements, company events such as stock splits and share buy backs, stock's past return performance, changes in macro liquidity, or to increased information asymmetry in times of greater uncertainty.[19] In this paper, we take changes in liquidity as given and the nature of liquidity shocks is beyond the scope of this paper. Nevertheless, we perform additional robustness checks through controlling for a well defined information event, earnings announcements.

Specifically, stocks that experience positive (negative) liquidity shocks may coincide with positive (negative) earnings shocks and it is well known that earnings shocks are followed by a post announcement drift (PEAD). To control for this effect, we follow Ball and Brown (1968) and Bernard and Thomas (1989, 1990) and define firm i's unexpected EPS (UE) in calendar quarter q of earnings announcement as:

$$UE_{i,q} = EPS_{i,q} - EPS_{i,q-4}, \tag{14}$$

where $EPS_{i,q}$ and $EPS_{i,q-4}$ are the firm's basic EPS excluding extraordinary items in quarters q and $q-4$, respectively. The firm's standardized unexpected earnings in quarter q (SUE_q) is calculated by scaling UE_q by its standard deviation over the past eight quarters (with a minimum of four UE observations available).[20] We then use SUE_q to predict stock returns in the following months before the firm's next earnings announcement.

[19] A stronger case of underreaction can be made for liquidity shocks compared to well-defined and easy-to-interpret information events such as earnings releases. Since liquidity changes are less clearly defined and its pricing implications are less obvious, investors are more likely to ignore this "news". The illusive and indirect nature of liquidity "news" suggests that underreaction to liquidity shocks can go above and beyond any underreaction to the direct events that trigger liquidity changes.

[20] Our results are robust to using net assets per share, net book value of equity per share, total liabilities per share, and price per share as the scaling variable.

We control for the PEAD effect by first sorting stocks into quintiles based on the standardized unexpected earnings measure (SUE), stocks within each SUE quintile are then sorted into quintiles on liquidity shock (LIQU). Table 15 reports the equal-weighted average returns for each of the 5×5 portfolios of the SUE and LIQU, the return difference (High$-$Low) between the highest and lowest LIQU quintiles within each SUE quintile, and the 3-factor alpha. After controlling for SUE, the return differences between the highest and the lowest LIQU quintiles within each SUE portfolio are in the range of 60 to 72 basis points per month, and remain significant at the 1% level based on the Newey-West adjusted t-statistics. The 3-factor alphas also tell a very similar story. Moreover, the High$-$Low return differentials are relatively stable across different SUE quintiles. The evidence thus suggests that the effect of liquidity shocks on future returns goes beyond the PEAD effect.

Generally speaking, if markets are rational and react to information promptly, these other value-relevant shocks (information releases and company events) should have been incorporated into prices already and any of their predictability should have been captured by the predictability of past returns. Our results remain significant after controlling for past returns, suggesting that these other factors alone can not explain our findings. For future work, it might be interesting to focus on concrete cases of liquidity shocks and study market's reactions to these particular episodes in an event study setting. One example of such events is stock splits. Muscarella and Vetsuypens (1996), Schultz (2000) and Lin, Singh, and Yu (2009) find that there has been considerable increases in trading volume and reduction in liquidity risk subsequent to stock splits. This suggests that stock splits increase the liquidity of the stocks and should lead to a reduction in risk premia. The implication is that, in a full efficient market in which investors react immediately and rationally to split announcements, share prices should rise instantaneously and future returns should be low. However, this is inconsistent with the findings in Ikenberry, Rankine, and Stice (1996) and Desai and Jain (1997), who document that prices continue to drift upwards up to one year following split announcements. Investigating stock market's underreaction to stock splits and the associated liquidity changes can potentially explain these findings.

Finally, we test whether investors are involved with market liquidity timing, which means when market liquidity is expected to decrease in the future, investors try to time this market event by reducing their exposure to future market liquidity. To investigate the presence and significance of market liquidity timing, we propose the following extension of the CAPM:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \gamma_i ILLIQ_{m,t} + \delta_i ILLIQ^2_{m,t} + \varepsilon_{i,t}, \tag{15}$$

where $ILLIQ_{m,t}$ is the market-wide illiquidity proxied by the Amihud's (2002) illiquidity measure, defined as the cross-sectional average monthly illiquidity of all stocks in CRSP, and $ILLIQ^2_{m,t}$ is the convexity adjustment. After we estimate the market beta (β_i), the market illiquidity beta (γ_i), and the liquidity timing beta (δ_i) using time-series observations over the past 60 months (or a minimum of 24 observations as available), we run the firm level Fama-MacBeth regressions with and without the control variables. The average slope coefficients of β_i, γ_i, and δ_i turn out to be statistically insignificant without any exception, implying no evidence for a liquidity timing activity of investors in the U.S. equity market.[21] These results thus indicate that investors' timing of systematic liquidity shocks does not contribute to the cross-sectional return predictability.

7. Conclusion

The liquidity of a stock refers to the degree to which a significant quantity can be traded in a short period without incurring a large transaction cost or adverse price impact. Given that the level of individual stock's illiquidity is positively priced in the cross-section of expected returns and that liquidity shocks are highly persistent, one would expect that negative liquidity shocks should lead to higher future returns if stock market reacts immediately and to the full extent to the increased risk premium.

[21] The market beta, the market illiquidity beta, and the liquidity timing beta in equations (13) and (15) are estimated using observations over past 60 months (or a minimum of 24 observations as available). At an earlier stage of the study, instead of using the level of $ILLIQ_{m,t}$, in equations (13) and (15), we use the change in market illiquidity, $\Delta ILLIQ_{m,t}$. Moreover, we use the innovations in market illiquidity obtained from the residuals of an AR(1) model. Similar to our findings from $ILLIQ_{m,t}$, the market illiquidity beta and the liquidity timing beta obtained from the change and innovations in market illiquidity do not predict the cross-sectional variation in stock returns.

On the contrary, we find a surprising positive relationship between firm level liquidity shocks and future returns: decile portfolios long stocks with positive liquidity shocks and short stocks with negative liquidity shocks generate a raw return of 1.2% in the subsequent month. This relation is statistically and economically significant and robust across alternative liquidity measures and after controlling for various risk factors and firm characteristics such as size, book-to-market, momentum, short-term reversal, analyst dispersion, level of illiquidity, liquidity risk, idiosyncratic volatility, and demand for extreme positive returns. The strong predictive power of liquidity shocks remains intact for non-crisis periods as well as recessionary and expansionary periods. The significantly positive link between liquidity shocks and future stock returns is also robust across the five decades in our sample.

We show that negative liquidity shocks not only lead to lower contemporaneous returns, they continue to predict negative returns for up to six months in the future. This evidence suggests that the stock market underreacts to firm level liquidity shocks. Negative and persistent liquidity shocks increase future risk premia and result in lower contemporaneous stock prices. However, when the market underreacts, the effect of the shock on lowering stock prices does not occur immediately, rather, the effect is gradually incorporated into prices over time, leading to a continuation of negative returns in the near future.

We explore two potential driving forces of this underreaction: investor inattention and illiquidity. We find that the return predictability of liquidity shocks is stronger among stocks that receive less investor attention (small stocks and stocks with low analyst coverage and institutional holdings) as well as among less liquid stocks. Our analyses suggest that both investor inattention and illiquidity can drive stock market underreactions to liquidity shocks, and these two mechanisms are significantly different from each other.

Our study contributes to the empirical literature on the effects of investor inattention on stock price dynamics by introducing a new liquidity dimension. Our findings also contribute to the literature on liquidity and stock returns by focusing on time series variations in liquidity and by providing the first piece of evidence of the stock market's underreaction to firm level liquidity shocks.

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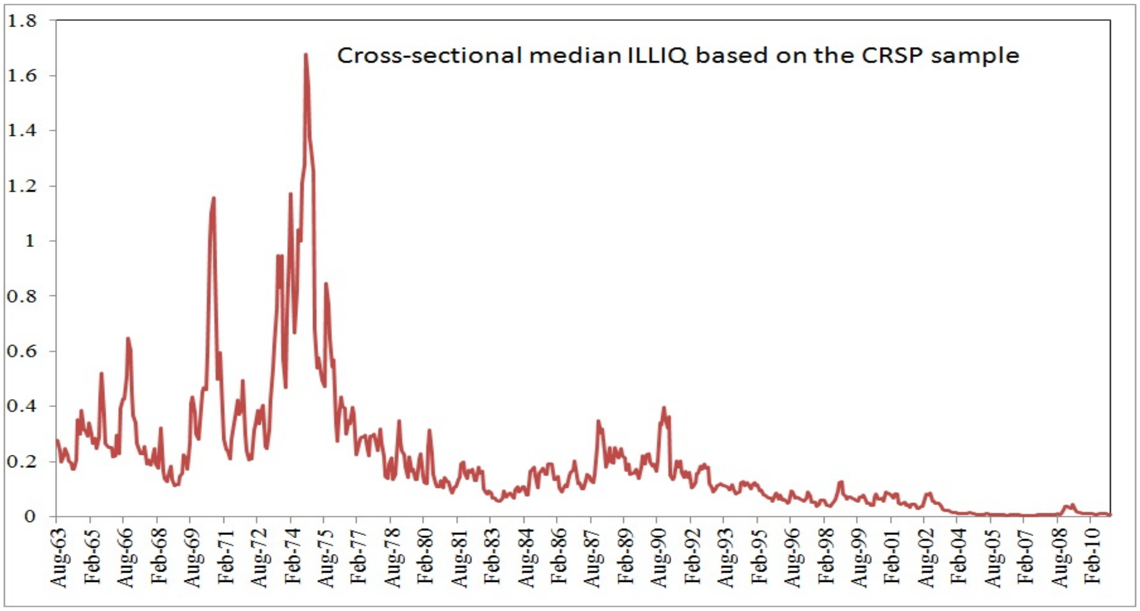

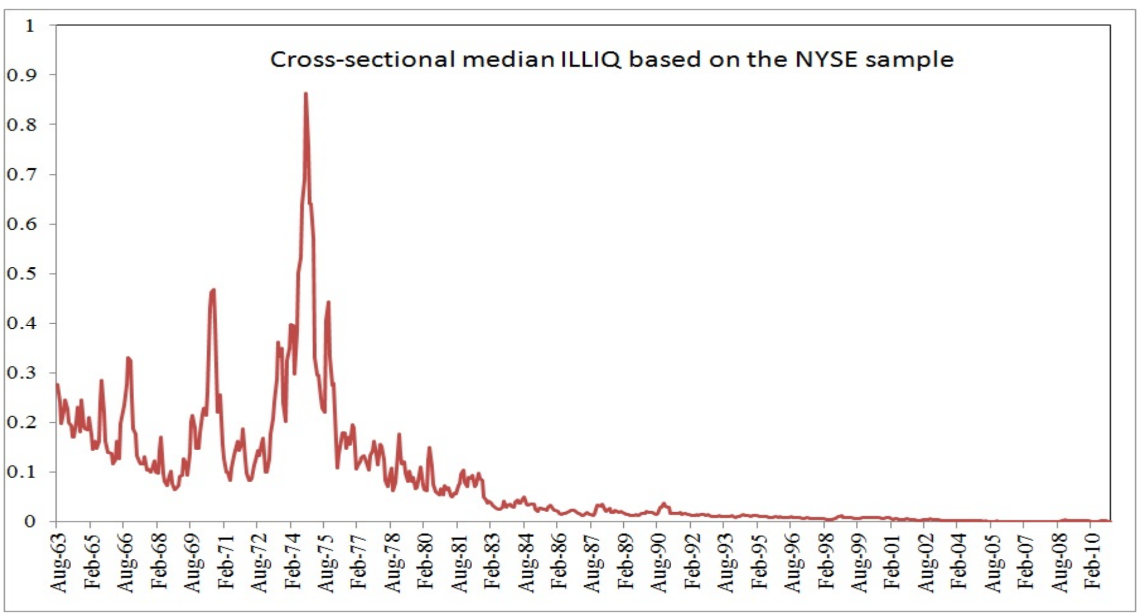

Figure 1. illiquidity level - Full sample. This figure depicts the cross-sectional medians of the monthly Amihud's illiquidity measure based on the CRSP sample (upper panel) and the NYSE sample (lower panel). The sample period is from August 1963 to December 2010.

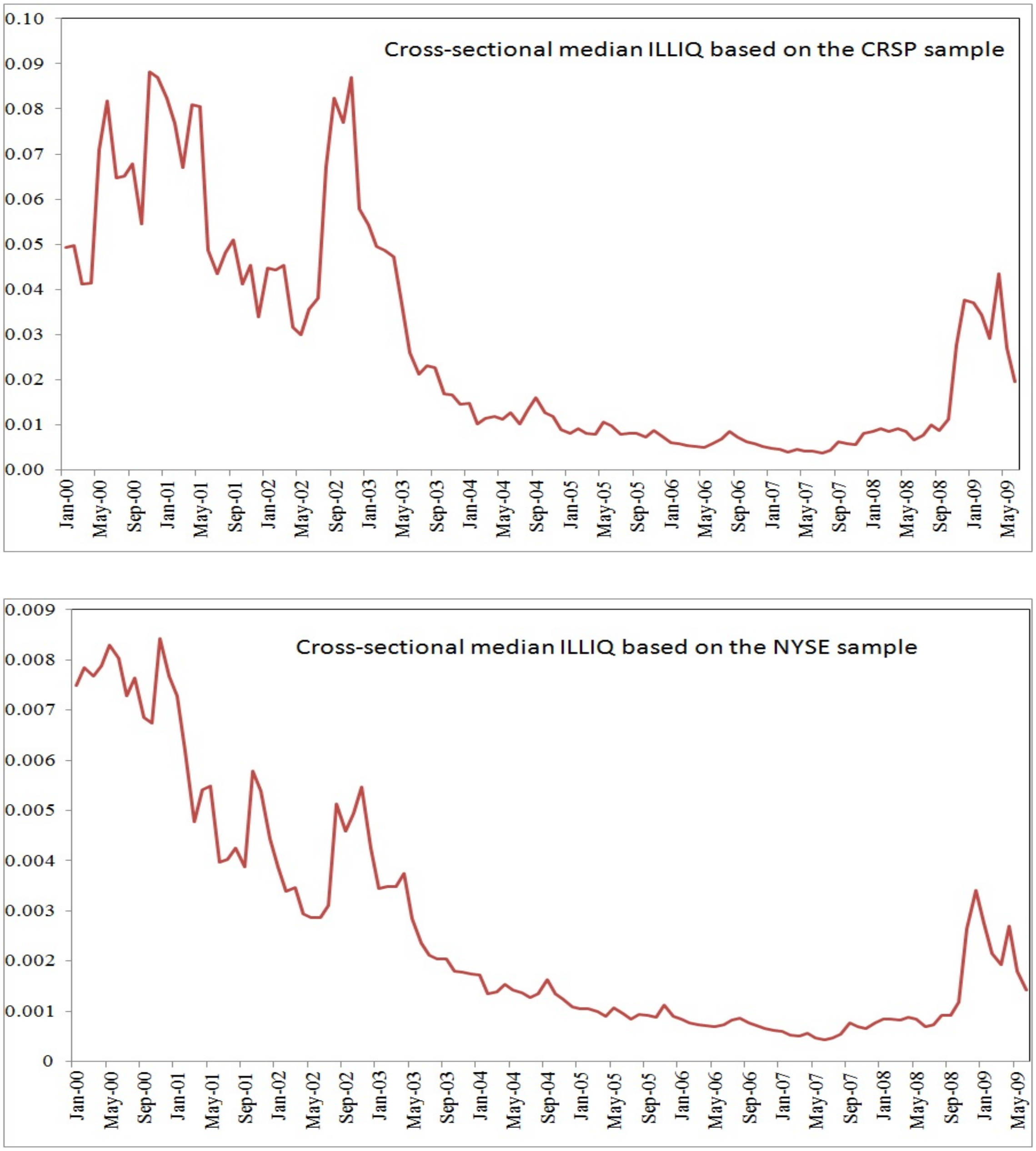

Figure 2. illiquidity level - Post decimalization. This figure depicts the cross-sectional medians of the monthly Amihud's illiquidity measure based on the CRSP sample (upper panel) and the NYSE sample (lower panel). The sample period is from January 2000 to December 2010.

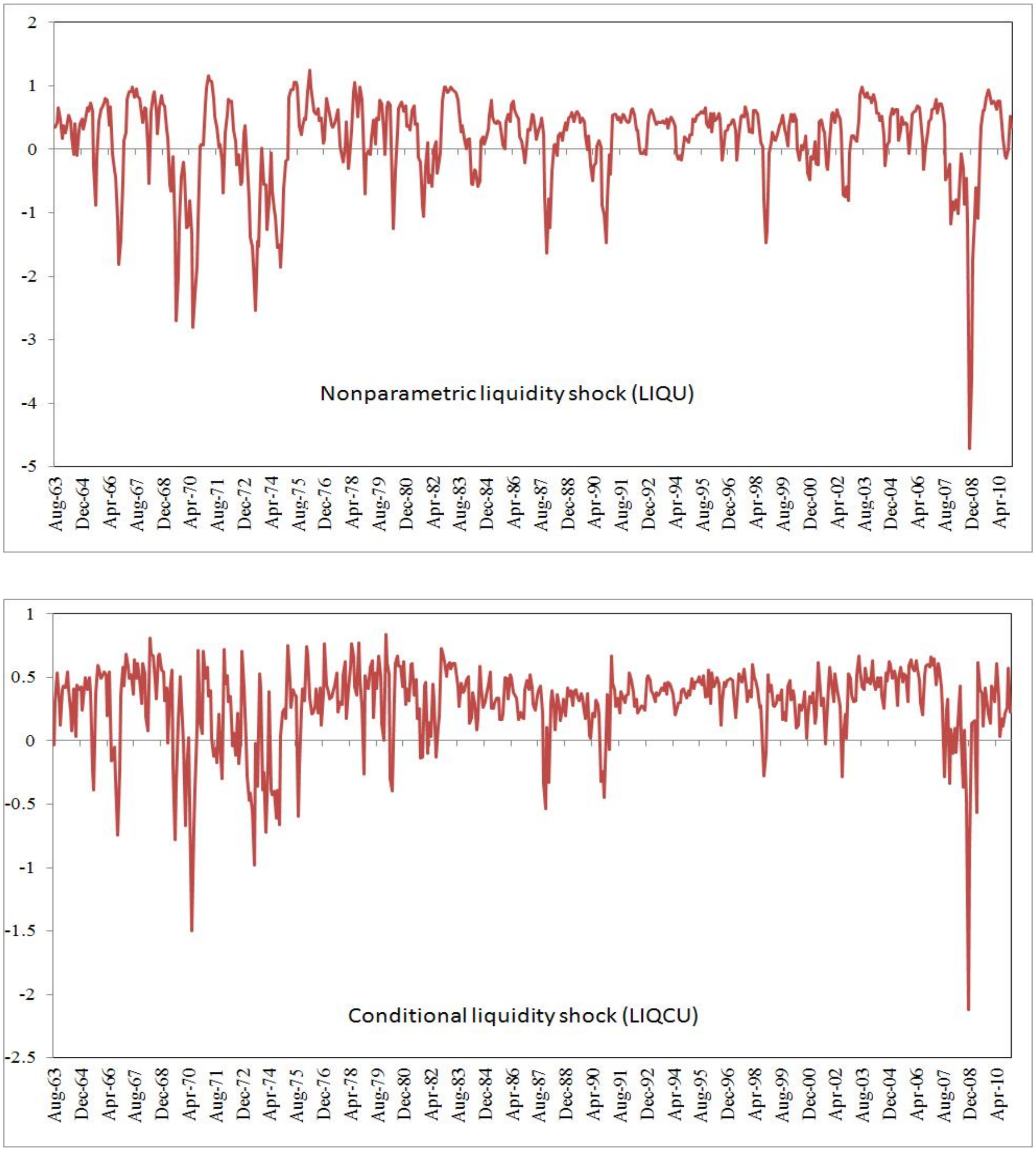

Figure 3. liquidity shock. The upper panel depicts the cross-sectional medians of the nonparametric liquidity shock (LIQU), defined as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. The lower panel depicts the cross-sectional medians of the conditional liquidity shock (LIQCU), estimated from the ARMA(1,1)-GARCH(1,1) specification using the monthly Amihud's illiquidity measure over the past five years. The sample period is from August 1963 to December 2010.

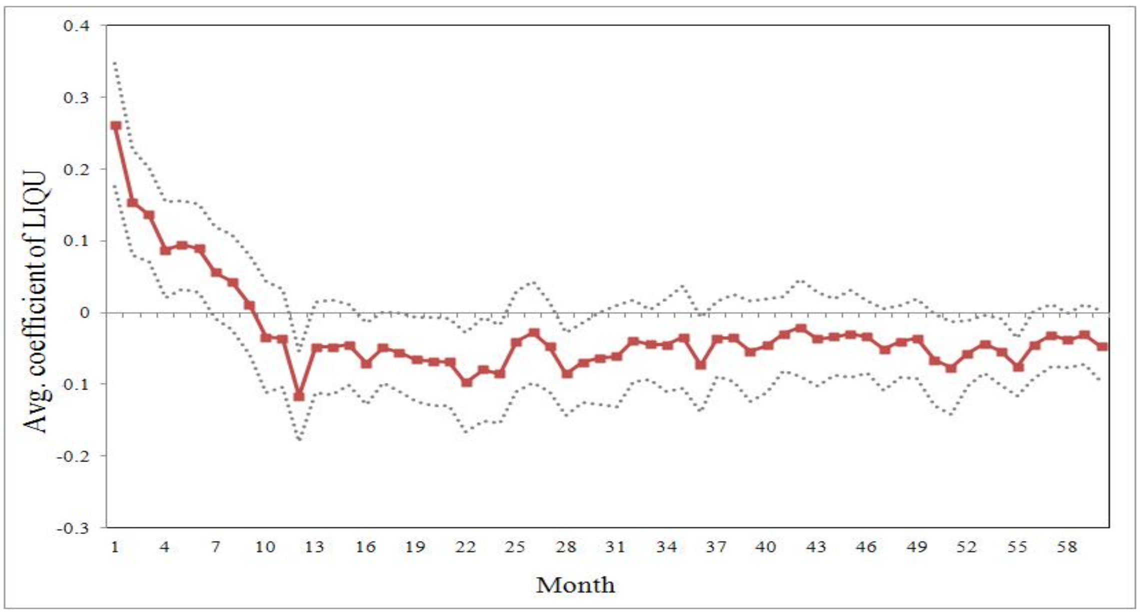

Figure 4. Stock market reactions to liquidity shocks over time. This figure depicts the average slope coefficients on liquidity shock (LIQU) from the monthly Fama-MacBeth regressions of stock returns for month $t+i$, where $i = 1, \ldots, 60$, against LIQU in month t. The dashed lines indicate the 95% confidence bounds, calculated based on the Newey-West robust standard errors.

Table 1
Descriptive statistics

Panel A reports the time-series averages of the cross-sectional mean, median, standard deviation, skewness and kurtosis of the main variables used in this paper. All the variables, except for RET, the return in month $t+1$, are computed for individual firms at the end of the portfolio formation month (month t). LIQU denotes the liquidity shock, defined as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. BETA, LNME, and LNBM denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. MOM is the momentum return. REV is the short-term reversal. COSKEW and IVOL are the co-skewness and idiosyncratic volatility, respectively. MAX denotes the maximum daily return in a month. DISP measures the analyst earnings forecast dispersion. PS is the Pastor and Stambaugh liquidity beta. SDTURN denotes the standard deviation of TURN over the past 12 months. CVILLIQ is the coefficient of variation in the Amihud's illiquidity measure. SDILLIQ is the standard deviation of ILLIQ over the past 12 months. CVRG denotes the natural logarithm of the number of analysts covering the firm. INST is the quarterly institutional ownership. Panel B reports time-series average of the monthly cross-sectional correlations (multiplied by 100) between the variables in our sample. The sample covers the period from August 1963 to December 2010.

Panel A. Summary statistics

	Mean	Median	Std. dev.	Skewness	Kurtosis
RET	1.197	0.250	14.728	2.289	42.736
ILLIQ	2.233	0.224	6.885	5.108	29.322
LIQU	-0.188	0.143	1.414	-1.658	4.290
BETA	1.416	1.287	0.906	1.252	15.340
LNME	4.771	4.640	1.852	0.321	-0.182
LNBM	-0.456	-0.373	0.807	-0.698	2.654
MOM	15.230	6.657	57.441	3.946	57.259
REV	1.295	0.268	14.416	2.398	35.661
COSKEW	-0.009	-0.008	0.092	0.722	20.445
IVOL	2.722	2.161	2.160	4.130	53.822
MAX	7.226	5.368	7.225	5.946	104.787
DISP	0.210	0.049	1.179	19.796	555.858
TURN	0.821	0.504	1.340	9.166	248.850
PS	-1.759	-1.005	40.263	-0.189	1.288
SDTURN	0.408	0.247	0.486	2.648	8.689
SDILLIQ	2.582	0.182	8.639	5.285	31.915
CVILLIQ	1.220	1.094	0.484	1.496	2.731
CVRG	1.843	1.813	0.779	0.124	-0.983
INST	0.359	0.336	0.254	0.371	-0.809

Table 1 – continued

Panel B: Correlations

	RET	ILLIQ	LIQU	BETA	LNME	LNBM	MOM	REV	CO-SKEW	IVOL	MAX	DISP	TURN	PS	SD-TURN	SD-ILLIQ	CV-ILLIQ	CVRG
ILLIQ	0.3																	
LIQU	3.1	-26.7																
BETA	-1.2	9.6	-5.0															
LNME	-0.3	-46.0	16.8	-25.7														
LNBM	2.9	14.7	-3.1	-8.5	-23.1													
MOM	3.2	-15.6	29.2	-0.3	13.7	-13.6												
REV	-4.5	-4.8	16.0	-0.7	5.2	1.9	1.3											
COSKEW	0.0	-4.2	1.6	3.6	9.8	4.0	0.4	0.9										
IVOL	-3.5	48.3	-16.9	30.3	-51.0	2.6	-13.0	13.1	-5.2									
MAX	-4.1	35.1	-9.5	25.6	-38.6	1.4	-10.1	32.3	-4.0	88.9								
DISP	-1.1	4.7	-5.3	6.4	-9.5	7.4	-7.2	-1.5	-0.4	11.5	8.9							
TURN	-1.4	-11.8	16.4	19.0	2.7	-11.9	17.4	14.8	1.3	24.0	25.1	3.2						
PS	0.4	-4.3	1.0	-7.1	3.4	1.7	1.2	1.1	-20.0	-6.2	-4.6	-0.8	-2.5					
SDTURN	-2.9	-6.2	0.7	28.4	-14.8	-11.7	17.6	1.8	-1.2	23.7	22.1	6.0	62.2	-3.6				
SDILLIQ	0.8	73.5	-6.9	11.4	-44.5	13.7	-4.2	1.9	-3.9	48.6	37.8	4.3	-5.8	-4.5	-1.1			
CVILLIQ	1.0	36.9	-16.4	0.5	-43.0	14.5	-10.7	1.6	-4.9	17.5	13.6	1.3	-13.9	0.1	-10.5	31.3		
CVRG	-0.7	-24.3	8.3	-14.9	76.9	-13.5	-1.8	-0.7	13.9	-28.5	-20.6	-5.3	9.8	-1.0	-5.7	-24.6	-34.6	
INST	1.2	-29.6	12.9	-7.8	66.0	-4.2	6.9	0.6	13.6	-34.9	-26.8	-4.9	16.6	0.8	1.6	-29.6	-35.7	47.2

Table 2
Raw and risk-adjusted returns on the liquidity shock portfolios

Each month, NYSE, AMEX, and NASDAQ stocks are sorted into ten decile portfolios based on liquidity shock (LIQU), defined as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. This table reports the average monthly returns in month $t+1$ and the 3-factor Fama-French (1993) alphas for each LIQU portfolio. Columns "Avg. LIQU" and "Avg. ILLIQ" report average LIQU and ILLIQ values for each decile portfolio. The last column shows the average market share of each portfolio. The last three rows show the differences in monthly returns between High and Low LIQU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles, and between decile 1 and the rest of deciles. Average returns and alphas are defined in monthly percentage terms. The entries in Panels A and B are based on the CRSP and NYSE decile breakpoints, respectively. Newey-West t-statistics are given in parentheses. The sample covers the period from August 1963 to December 2010.

Panel A: CRSP breakpoints

Decile	Avg. RET	Alpha	Avg. LIQU	Avg. ILLIQ	Mkt. shr.
1 (Low)	0.35	-0.94	-3.39	6.78	5.76%
	(-0.27)	(-5.69)			
2	0.75	-0.54	-1.38	3.47	8.37%
	(0.95)	(-4.64)			
3	1.03	-0.27	-0.72	2.73	9.38%
	(1.91)	(-2.94)			
4	1.06	-0.24	-0.30	2.24	9.69%
	(2.05)	(-2.95)			
5	1.21	-0.07	0.01	1.87	9.82%
	(2.58)	(-0.91)			
6	1.30	0.01	0.26	1.61	9.28%
	(2.86)	(0.20)			
7	1.50	0.28	0.49	1.37	9.19%
	(3.65)	(2.50)			
8	1.58	0.35	0.71	1.09	10.00%
	(3.98)	(4.88)			
9	1.60	0.40	0.97	0.84	11.54%
	(4.22)	(5.59)			
10 (High)	1.58	0.48	1.47	0.54	16.98%
	(4.45)	(5.25)			
High-Low	1.23	1.42			
	(5.86)	(6.67)			
High-the rest	0.42	0.59			
	(3.64)	(5.32)			
Low-the rest	-0.94	-0.99			
	(-7.16)	(-6.95)			

Table 2 – continued

Panel B: NYSE breakpoints

Decile	Avg. RET	Alpha	Avg. LIQU	Avg. ILLIQ	Mkt. shr.
1 (Low)	0.40	-0.90	-3.02	6.04	7.30%
	(-0.12)	(-6.02)			
2	0.87	-0.43	-1.16	3.12	8.66%
	(1.35)	(-4.19)			
3	0.96	-0.35	-0.60	2.52	9.45%
	(1.71)	(-3.49)			
4	1.15	-0.14	-0.23	2.07	9.61%
	(2.41)	(-1.69)			
5	1.23	-0.06	0.05	1.75	9.97%
	(2.67)	(-0.68)			
6	1.35	0.07	0.30	1.51	9.75%
	(3.09)	(0.88)			
7	1.51	0.26	0.53	1.28	9.87%
	(3.81)	(2.91)			
8	1.61	0.37	0.76	1.04	10.40%
	(4.14)	(5.27)			
9	1.57	0.38	1.04	0.80	11.36%
	(4.14)	(5.14)			
10 (High)	1.58	0.48	1.54	0.53	13.64%
	(4.51)	(5.14)			
High-Low	1.18	1.38			
	(5.86)	(6.83)			
High-the rest	0.40	0.57			
	(3.38)	(4.93)			
Low-the rest	-0.91	-0.96			
	(-7.55)	(-7.57)			

Table 3
Portfolio characteristics

Each month, NYSE, AMEX, and NASDAQ stocks are sorted into ten decile portfolios based on liquidity shock (LIQU), defined as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. This table presents the average across the months in the sample of the average values within each month of various characteristics for the stocks in each decile. Average values are reported for liquidity shock (LIQU), the log market capitalization (LNME), the book-to-market ratio (BM), the market beta (BETA), the Amihud's illiquidity measure (ILLIQ), the price (in dollars), the return over the 11 months prior to portfolio formation (MOM), the return in the portfolio formation month (REV), the monthly co-skewness (COSKEW), the monthly idiosyncratic volatility (IVOL), the maximum daily return in a month (MAX), and the analyst dispersion (DISP).

	LIQU	LNME	BM	BETA	ILLIQ	PRICE	MOM	REV	COSKEW	IVOL	MAX	DISP
1 (Low)	-3.39	4.10	1.01	1.48	6.78	18.71	-16.41	-2.57	-0.013	3.68	9.22	0.37
2	-1.38	4.56	0.96	1.45	3.47	22.67	-7.44	-1.20	-0.010	2.99	7.67	0.28
3	-0.72	4.68	0.94	1.44	2.73	25.00	-0.09	-0.46	-0.009	2.82	7.29	0.24
4	-0.30	4.71	0.94	1.44	2.24	26.68	7.47	0.19	-0.009	2.73	7.14	0.22
5	0.01	4.73	0.91	1.45	1.87	26.80	15.79	0.79	-0.009	2.68	7.06	0.20
6	0.26	4.74	0.91	1.45	1.61	25.93	23.35	1.43	-0.010	2.65	7.07	0.19
7	0.49	4.79	0.89	1.44	1.37	26.49	29.92	2.21	-0.009	2.59	7.00	0.18
8	0.71	4.89	0.88	1.41	1.09	26.95	33.95	2.94	-0.010	2.51	6.86	0.18
9	0.97	5.06	0.88	1.36	0.84	29.38	34.82	3.99	-0.008	2.40	6.68	0.16
10 (High)	1.47	5.44	0.86	1.24	0.54	41.64	30.89	5.62	-0.005	2.18	6.27	0.15

Table 4
Bivariate portfolio sorts

This table reports the equal-weighted returns and return differences in month $t+1$ between high and low liquidity shock (LIQU) quintile portfolios and the corresponding 3-factor alphas after controlling for a given firm characteristics. LIQU is computed as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. BETA, LNME, and LNBM denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. MOM is the momentum return. DISP measures the analyst earnings forecast dispersion. COSKEW and IVOL are the co-skewness and idiosyncratic volatility, respectively. MAX denotes the maximum daily return in a month. REV is the short-term reversal. All the conditioning variables are measured in month t unless otherwise stated. In Panel A, stocks are first sorted into control variable quintiles and then, within each control variable quintile, into LIQU quintiles. In Panel B, stocks are independently sorted into control variable and LIQU quintiles. Panels report average returns of the LIQU quintile portfolios, averaged across the five control quintiles to produce quintile portfolios with dispersion in LIQU but with similar levels of the control variable. Newey-West t-statistics are reported in parentheses.

Panel A. Dependent bivariate sorts

Quintile	BETA	LNME	LNBM	MOM	REV	COSKEW	IVOL	MAX	DISP
1 (Low)	0.67	0.58	0.61	0.81	0.40	0.67	0.68	0.67	0.80
2	1.08	1.01	1.03	1.09	1.03	1.06	1.03	1.04	1.06
3	1.32	1.25	1.28	1.25	1.28	1.33	1.24	1.23	1.26
4	1.53	1.47	1.55	1.40	1.60	1.52	1.44	1.47	1.42
5 (High)	1.60	1.66	1.59	1.44	1.66	1.60	1.59	1.57	1.54
High-Low	0.93	1.07	0.98	0.63	1.26	0.93	0.91	0.90	0.74
	(7.07)	(7.28)	(6.29)	(5.48)	(8.21)	(5.75)	(7.17)	(6.67)	(3.65)
Alpha	1.07	1.18	1.10	0.70	1.40	1.07	1.01	1.03	0.90
	(8.16)	(7.54)	(6.97)	(5.65)	(9.49)	(6.51)	(7.54)	(7.24)	(4.63)

Panel B. Independent bivariate sorts

Quintile	BETA	LNME	LNBM	MOM	REV	COSKEW	IVOL	MAX	DISP
1 (Low)	0.66	0.59	0.60	0.82	0.31	0.63	0.67	0.67	0.80
2	1.09	1.03	1.01	1.11	0.96	1.09	1.04	1.05	1.11
3	1.28	1.24	1.28	1.23	1.25	1.29	1.24	1.24	1.25
4	1.56	1.55	1.56	1.44	1.57	1.57	1.51	1.51	1.44
5 (High)	1.62	1.68	1.58	1.47	1.67	1.61	1.63	1.61	1.57
High-Low	0.96	1.10	0.97	0.65	1.37	0.98	0.96	0.94	0.77
	(7.04)	(7.13)	(6.21)	(5.27)	(8.59)	(5.99)	(7.31)	(6.90)	(3.72)
Alpha	1.11	1.21	1.10	0.69	1.49	1.13	1.06	1.06	0.93
	(8.06)	(7.59)	(6.98)	(5.20)	(9.59)	(6.74)	(7.63)	(7.30)	(4.69)

Table 5
Firm-level cross-sectional regressions

Monthly excess stock returns are regressed on a set of lagged predictive variables using the Fama and MacBeth (1973) methodology. This table reports the average slope coefficients. LIQU is computed as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. BETA, LNME, and LNBM denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. MOM is the momentum return. REV is the short-term reversal. COSKEW and IVOL are the co-skewness and idiosyncratic volatility, respectively. MAX denotes the maximum daily return in a month. DISP measures the analyst earnings forecast dispersion. Newey-West t-statistics are reported in parentheses.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
LIQU	0.260	0.196	0.250	0.262	0.246	0.253	0.227	0.294	0.198	0.186	0.195	0.164
	(8.99)	(7.78)	(12.84)	(9.16)	(8.70)	(9.00)	(6.45)	(12.88)	(7.86)	(7.51)	(7.97)	(5.52)
BETA	0.088	0.064	0.111	0.093	0.165	0.193	0.085	0.086	0.069	0.133	0.160	0.059
	(0.87)	(0.69)	(0.97)	(0.91)	(1.74)	(1.97)	(0.63)	(0.81)	(0.74)	(1.51)	(1.75)	(0.49)
LNME	-0.152	-0.163	-0.127	-0.150	-0.224	-0.225	-0.121	-0.137	-0.163	-0.231	-0.232	-0.135
	(-3.45)	(-3.81)	(-2.83)	(-3.41)	(-5.85)	(-5.55)	(-2.87)	(-3.13)	(-3.82)	(-6.18)	(-5.86)	(-3.26)
LNBM	0.273	0.306	0.289	0.276	0.243	0.246	0.139	0.313	0.309	0.280	0.276	0.210
	(3.68)	(4.45)	(3.79)	(3.73)	(3.44)	(3.42)	(1.44)	(4.43)	(4.49)	(4.26)	(4.15)	(2.41)
MOM		0.007						0.006	0.007	0.007	0.006	0.008
		(5.08)						(4.00)	(5.16)	(4.79)	(4.51)	(4.01)
REV			-0.066					-0.066				
			(-14.00)					(-14.11)				
COSKEW				-0.950					-0.568			
				(-1.51)					(-0.94)			
IVOL					-0.206					-0.205		
					(-5.57)					(-5.72)		
MAX						-0.082					-0.082	
						(-8.17)					(-8.51)	
DISP							-0.190					-0.160
							(-2.54)					(-2.30)

Table 6
Controlling for other liquidity-related variables

Panel A reports average returns of the LIQU quintile portfolios, averaged across the five quintiles of liquidity-based control variables to produce quintile portfolios with dispersion in LIQU but with similar levels of the control variable. The conditioning variables are measured with a lag. The last two rows in Panel A show the 5 – 1 return differences and the corresponding 3-factor alphas from the dependent sorts of the liquidity-based control variables and LIQU. Panel B reports the average slope coefficients from the monthly predictive regressions of excess returns on a set of lagged predictive variables. LIQU is computed as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. BETA, LNME, and LNBM denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. MOM is the momentum return. PS is the Pastor and Stambaugh liquidity exposure. CVILLIQ is the coefficient of variation in the Amihud's illiquidity measure. MILLIQ and SDILLIQ are the mean and standard deviation of ILLIQ over the past 12 months. SDTURN denotes the standard deviation of monthly share turnover over the past 12 months. Newey-West adjusted t-statistics are given in parentheses.

Panel A. Dependent bivariate sorts

Quintile	ILLIQ	MILLIQ	SDILLIQ	CVILLIQ	PS	SDTURN
1 (Low)	0.54	0.67	0.62	0.53	0.61	0.58
2	0.97	1.07	1.01	1.03	1.03	1.07
3	1.28	1.25	1.21	1.27	1.26	1.27
4	1.46	1.47	1.47	1.51	1.48	1.50
5 (High)	1.67	1.66	1.68	1.62	1.56	1.56
High-Low	1.12	0.99	1.06	1.09	0.95	0.98
	(7.25)	(6.23)	(6.71)	(6.39)	(5.69)	(6.28)
Alpha	1.17	1.12	1.18	1.24	1.11	1.15
	(7.06)	(6.73)	(7.13)	(7.03)	(6.59)	(7.60)

Panel B. Monthly predictive regressions

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LIQU	0.236	0.182	0.194	0.200	0.198	0.185
	(9.00)	(7.53)	(7.87)	(7.98)	(7.47)	(7.36)
BETA	0.077	0.072	0.062	0.071	0.027	0.143
	(0.83)	(0.77)	(0.68)	(0.78)	(0.26)	(1.70)
LNME	-0.111	-0.113	-0.110	-0.135	-0.150	-0.189
	(-2.74)	(-2.90)	(-2.75)	(-2.99)	(-3.53)	(-4.48)
LNBM	0.299	0.307	0.305	0.299	0.313	0.261
	(4.30)	(4.44)	(4.45)	(4.38)	(4.42)	(3.98)
MOM	0.007	0.007	0.007	0.007	0.006	0.008
	(5.16)	(4.94)	(4.85)	(5.31)	(4.38)	(5.97)
ILLIQ	0.096					
	(3.61)					
MILLIQ		0.053				
		(3.21)				
SDILLIQ			0.060			
			(2.68)			
CVILLIQ				0.229		
				(3.57)		
PS					0.001	
					(1.81)	
SDTURN						-1.044
						(-5.83)

Table 7
Contemporaneous relation between liquidity shocks and expected returns

Panel A reports the average contemporaneous monthly returns and the 3-factor Fama and French (1993) alphas on decile portfolios sorted by liquidity innovations. Each month, NYSE, AMEX, and NASDAQ stocks are sorted into ten decile portfolios based on liquidity shock (LIQU), defined as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. The last three rows show the differences in monthly returns between High and Low LIQU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles, and between decile 1 and the rest of deciles. Average returns and alphas are defined in monthly percentage terms. Panel B reports the average slope coefficients from the monthly regressions of excess returns on contemporaneous liquidity shocks and a set of lagged predictive variables using the Fama-MacBeth methodology. BETA, LNME, and LNBM denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. MOM is the momentum return. REV is the short-term reversal. COSKEW and IVOL are the idiosyncratic skewness and idiosyncratic volatility, respectively. DISP measures the analyst earnings forecast dispersion. MAX denotes the maximum daily return in a month. PS is the Pastor and Stambaugh liquidity exposure. SDTURN denotes the standard deviation of TURN over the past 12 months. CVILLIQ is the coefficient of variation in the Amihud illiquidity. SDILLIQ is the standard deviation of ILLIQ over the past 12 months. Newey-West t-statistics are given in parentheses. The sample covers the period from August 1963 to December 2010.

Panel A: Univariate portfolio sorts

Decile	Avg. RET	Alpha	Avg. LIQU	Mkt. shr.
1 (Low)	-2.57	-3.89	-3.39	5.76%
	(-8.35)	(-21.67)		
2	-1.20	-2.49	-1.38	8.37%
	(-5.23)	(-19.69)		
3	-0.46	-1.74	-0.72	9.38%
	(-3.01)	(-15.22)		
4	0.19	-1.10	-0.30	9.69%
	(-0.84)	(-10.68)		
5	0.79	-0.49	0.01	9.82%
	(1.15)	(-5.02)		
6	1.43	0.16	0.26	9.28%
	(3.23)	(1.90)		
7	2.21	0.95	0.49	9.19%
	(5.68)	(10.02)		
8	2.94	1.72	0.71	10.00%
	(8.08)	(16.15)		
9	3.99	2.81	0.97	11.54%
	(11.32)	(22.78)		
10 (High)	5.62	4.57	1.47	16.98%
	(18.17)	(30.42)		
High-Low	8.18	8.45		
	(29.15)	(30.02)		
High-the rest	4.80	5.02		
	(28.56)	(29.90)		
Low-the rest	-4.29	-4.38		
	(-23.28)	(-23.53)		

Table 7 – continued

Panel B: Monthly contemporaneous regressions

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
LIQU	2.313	1.759	2.193	2.205	1.742	2.151	2.184	2.171	2.176	2.186	2.177
	(31.02)	(26.42)	(31.86)	(31.70)	(25.58)	(31.22)	(31.10)	(31.28)	(31.14)	(32.80)	(31.36)
BETA	0.058	0.077	0.121	0.153	0.058	0.061	0.033	0.037	0.031	0.000	0.135
	(0.55)	(0.89)	(1.40)	(1.70)	(0.50)	(0.67)	(0.37)	(0.41)	(0.35)	(0.00)	(1.64)
LNME	-0.248	-0.339	-0.348	-0.355	-0.184	-0.211	-0.253	-0.222	-0.287	-0.270	-0.313
	(-5.49)	(-7.80)	(-9.23)	(-8.61)	(-4.27)	(-5.23)	(-6.24)	(-5.67)	(-6.13)	(-6.09)	(-7.20)
LNBM	0.396	0.242	0.348	0.344	0.304	0.373	0.380	0.372	0.374	0.389	0.321
	(5.72)	(3.75)	(5.45)	(5.34)	(3.59)	(5.55)	(5.71)	(5.56)	(5.66)	(5.69)	(5.08)
MOM	0.003	-0.002	0.003	0.003	0.004	0.004	0.004	0.004	0.004	0.003	0.005
	(2.07)	(-1.12)	(2.33)	(2.04)	(2.18)	(2.92)	(2.70)	(2.64)	(2.82)	(1.91)	(3.77)
REV	-0.080										
	(-16.91)										
COSKEW		-0.493									
		(-1.01)									
IVOL			-0.224								
			(-6.33)								
MAX				-0.091							
				(-9.11)							
DISP					-0.113						
					(-1.74)						
ILLIQ						0.095					
						(3.72)					
MILLIQ							0.017				
							(0.94)				
SDILLIQ								0.067			
								(2.67)			
CVILLIQ									0.009		
									(0.13)		
PS										0.001	
										(0.62)	
SDTURN											-1.211
											(-6.77)

Table 8

Returns on liquidity shock portfolios after controlling for investor attention

Stocks are sorted into quintile portfolios based on an investor attention variable and then into quintile portfolios of liquidity shock (LIQU) within each investor attention quintile using NYSE breakpoints. The investor attention variables are the natural logarithm of market capitalization (LNME), the number of analysts covering the firms (CVRG), and the quarterly aggregate institutional holdings (INST). This table reports the average returns for each of the 5×5 portfolios of LIQU and the investor attention variable, the High−Low return differences between High and Low LIQU quintile portfolios within each quintile portfolio of the investor attention variable, and the corresponding 3-factor alphas. The last column presents the $5-1$ average return differences for the investor attention variable within each LIQU quintile portfolio. Newey-West t-statistics are given in parentheses.

Panel A. Controlling for size

	LNME 1	2	3	4	LNME 5	LNME 5 − LNME 1
LIQU 1	0.53	0.73	0.78	0.86	0.66	0.13
2	1.12	1.08	1.09	0.92	0.85	-0.27
3	1.39	1.25	1.19	1.10	0.97	-0.42
4	1.69	1.52	1.42	1.25	0.99	-0.70
LIQU 5	1.96	1.66	1.40	1.27	1.06	-0.90
High - Low	1.43	0.93	0.62	0.41	0.40	-1.03
	(8.21)	(5.02)	(4.01)	(2.88)	(2.93)	(-7.07)
Alpha	1.53	1.07	0.74	0.55	0.50	-1.03
	(8.10)	(5.72)	(4.81)	(3.75)	(3.54)	(-6.69)

Panel B. Controlling for analyst coverage

	CVRG 1	2	3	4	CVRG 5	CVRG 5 - CVRG 1
LIQU 1	0.54	0.82	0.89	1.00	0.88	0.34
2	0.99	1.05	1.28	1.17	1.02	0.03
3	1.43	1.34	1.16	1.12	1.09	-0.34
4	1.64	1.51	1.39	1.29	1.20	-0.44
LIQU 5	1.92	1.64	1.47	1.28	1.11	-0.81
High - Low	1.38	0.82	0.58	0.29	0.23	-1.15
	(5.72)	(3.28)	(2.51)	(1.11)	(0.97)	(-6.20)
Alpha	1.53	1.05	0.83	0.53	0.38	-1.16
	(6.46)	(4.66)	(3.80)	(2.29)	(1.61)	(-5.96)

Panel C. Controlling for institutional holdings

	INST 1	2	3	4	INST 5	INST 5 - INST 1
LIQU 1	0.22	0.58	0.91	0.89	0.84	0.62
2	0.79	1.01	1.18	1.03	0.93	0.14
3	1.13	1.21	1.10	1.16	1.28	0.15
4	1.42	1.48	1.43	1.47	1.25	-0.17
LIQU 5	1.82	1.65	1.53	1.42	1.19	-0.63
High - Low	1.60	1.07	0.63	0.52	0.35	-1.25
	(6.37)	(3.67)	(2.51)	(2.21)	(1.50)	(-5.93)
Alpha	1.73	1.37	0.96	0.87	0.66	-1.05
	(6.24)	(5.17)	(4.20)	(4.07)	(3.12)	(-5.23)

Table 9
Returns on liquidity shock portfolios after controlling for the level of illiquidity

Stocks are sorted into quintile portfolios based on the Amihud's illiquidity (ILLIQ) and then into quintile portfolios of liquidity shock (LIQU) within each ILLIQ quintile using NYSE breakpoints. This table reports the average returns for each of the 5×5 portfolios of ILLIQ and LIQU, the High$-$Low return differences between High and Low LIQU quintile portfolios within each ILLIQ quintile portfolio, and the corresponding 3-factor alphas. The last column presents the $5-1$ average return differences for the Amihud's illiquidity within each LIQU quintile portfolio. Newey-West t-statistics are given in parentheses.

	ILLIQ 1	2	3	4	ILLIQ 5	ILLIQ 5 - ILLIQ 1
LIQU 1	0.70	0.82	0.79	0.67	0.42	-0.29
2	0.97	0.99	1.05	1.00	1.06	0.08
3	1.46	1.14	1.23	1.17	1.36	-0.10
4	1.07	1.20	1.53	1.49	1.65	0.58
LIQU 5	1.18	1.24	1.49	1.84	1.92	0.73
High - Low	0.48	0.43	0.70	1.17	1.50	1.02
	(3.30)	(2.66)	(3.88)	(5.32)	(8.97)	(6.76)
Alpha	0.53	0.56	0.74	1.24	1.52	0.99
	(3.56)	(3.57)	(4.16)	(5.36)	(8.38)	(6.21)

Table 10
Triple sorted portfolio returns sequentially sorted by the level of illiquidity, investor attention and liquidity shocks

Stocks are first sorted into quintile portfolios based on the Amihud's illiquidity (ILLIQ); stocks within each ILLIQ quintile are further sorted into quintile portfolios based on one attention variable; stocks within each of the 25 ILLIQ and attention variable groupings are sorted into quintiles based on the liquidity shock (LIQU) using NYSE breakpoints. The investor attention variables are the natural logarithm of market capitalization (LNME), the number of analysts covering the firms (CVRG), and the quarterly aggregate institutional holdings (INST). This table reports the average returns for each of the 5×5 portfolios of the investor attention variable and LIQU by averaging returns across the quintiles of the Amihud's illiquidity, the High$-$Low return differences between High and Low LIQU quintile portfolios within each quintile portfolio of the investor attention variable, and the corresponding 3-factor alphas. The last column presents the $5-1$ average return differences for the investor attention variable within each LIQU quintile portfolio. Newey-West t-statistics are given in parentheses.

Panel A. Use LNME to proxy for investor attention

	LNME 1	2	3	4	LNME 5	LNME 5 $-$ LNME 1
LIQU 1	0.66	0.54	0.63	0.62	0.63	-0.04
2	1.20	0.95	0.98	0.88	0.81	-0.39
3	1.49	1.16	1.16	1.06	0.93	-0.55
4	1.64	1.47	1.33	1.26	1.01	-0.63
LIQU 5	1.85	1.69	1.53	1.39	1.19	-0.65
High - Low	1.18	1.15	0.90	0.77	0.56	-0.62
	(6.91)	(6.57)	(6.91)	(5.68)	(5.35)	(-4.33)
Alpha	1.29	1.27	1.00	0.86	0.62	-0.67
	(7.02)	(7.38)	(7.64)	(6.38)	(6.12)	(-4.26)

Panel B. Use CVRG to proxy for investor attention

	CVRG 1	2	3	4	CVRG 5	CVRG 5 - CVRG 1
LIQU 1	0.58	0.67	0.86	0.81	0.86	0.28
2	1.10	1.05	1.00	1.08	1.03	-0.07
3	1.22	1.27	1.13	1.12	1.24	0.02
4	1.62	1.50	1.25	1.33	1.27	-0.35
LIQU 5	1.83	1.68	1.56	1.68	1.42	-0.41
High - Low	1.25	1.01	0.70	0.87	0.56	-0.69
	(6.26)	(6.01)	(4.07)	(4.21)	(2.25)	(-3.47)
Alpha	1.35	1.11	0.78	0.98	0.64	-0.71
	(6.81)	(6.42)	(4.71)	(5.05)	(2.88)	(-3.71)

Panel C. Use INST to proxy for investor attention

	INST 1	2	3	4	INST 5	INST 5 - INST 1
LIQU 1	0.14	0.50	0.58	0.68	0.63	0.49
2	0.67	1.06	1.13	1.13	0.83	0.17
3	0.75	1.24	1.28	1.12	1.05	0.29
4	1.20	1.49	1.47	1.36	1.25	0.05
LIQU 5	1.65	1.87	1.77	1.64	1.35	-0.31
High - Low	1.52	1.36	1.20	0.96	0.71	-0.80
	(5.99)	(5.88)	(5.55)	(4.71)	(3.45)	(-3.89)
Alpha	1.63	1.53	1.37	1.16	0.89	-0.73
	(6.06)	(6.70)	(6.23)	(6.26)	(4.30)	(-3.38)

Table 11
Triple sorted portfolio returns sequentially sorted by investor attention, level of illiquidity, and liquidity shocks

Stocks are first sorted into quintile portfolios based on one investor attention variable; stocks within each investor attention quintile are further sorted into quintile portfolios based on the Amihud's illiquidity (ILLIQ); stocks within each of the 25 attention variable and ILLIQ groupings are sorted into quintiles based on the liquidity shock (LIQU) using NYSE breakpoints. The investor attention variables are the natural logarithm of market capitalization (LNME), the number of analysts covering the firms (CVRG), and the quarterly aggregate institutional holdings (INST). This table reports the average returns for each of the 5×5 portfolios of ILLIQ and LIQU, the High$-$Low return differences between High and Low LIQU quintile portfolios within each ILLIQ quintile portfolio, and the corresponding 3-factor alphas. The last column presents the $5-1$ average return differences for the Amihud's illiquidity within each LIQU quintile portfolio. Newey-West t-statistics are given in parentheses.

Panel A. Use LNME to proxy for investor attention

	ILLIQ 1	2	3	4	ILLIQ 5	ILLIQ 5 - ILLIQ 1
LIQU 1	0.69	0.68	0.61	0.48	0.42	-0.26
2	1.15	1.03	0.94	0.87	0.91	-0.24
3	1.40	1.22	1.20	1.04	1.20	-0.20
4	1.43	1.50	1.37	1.36	1.31	-0.12
LIQU 5	1.55	1.64	1.53	1.64	1.68	0.13
High - Low	0.87	0.96	0.92	1.16	1.26	0.39
	(4.00)	(5.34)	(6.38)	(7.52)	(8.23)	(1.87)
Alpha	1.05	1.09	0.98	1.23	1.24	0.19
	(4.89)	(5.77)	(6.35)	(7.49)	(7.42)	(0.95)

Panel B. Use CVRG to proxy for investor attention

	ILLIQ 1	2	3	4	ILLIQ 5	ILLIQ 5 - ILLIQ 1
LIQU 1	0.87	0.67	0.85	0.85	0.50	-0.37
2	1.08	0.95	1.13	1.15	1.01	-0.07
3	1.21	1.27	1.17	1.24	1.28	0.06
4	1.23	1.49	1.32	1.41	1.39	0.16
LIQU 5	1.32	1.43	1.71	1.72	1.85	0.54
High - Low	0.44	0.76	0.86	0.87	1.36	0.91
	(2.73)	(3.71)	(4.60)	(4.53)	(6.19)	(4.83)
Alpha	0.55	0.81	0.91	0.98	1.45	0.91
	(3.45)	(3.91)	(4.90)	(5.00)	(7.25)	(4.84)

Panel C. Use INST to proxy for investor attention

	ILLIQ 1	2	3	4	ILLIQ 5	ILLIQ 5 - ILLIQ 1
LIQU 1	0.65	0.60	0.64	0.33	0.33	-0.32
2	0.84	1.07	0.77	0.91	0.93	0.08
3	1.46	0.98	1.03	1.15	1.16	-0.31
4	1.08	1.36	1.42	1.50	1.34	0.26
LIQU 5	1.07	1.43	1.67	1.77	1.71	0.64
High - Low	0.42	0.83	1.03	1.45	1.38	0.96
	(1.82)	(2.98)	(3.57)	(6.47)	(6.33)	(4.17)
Alpha	0.57	0.99	1.20	1.59	1.51	0.95
	(2.55)	(3.28)	(3.85)	(6.76)	(6.78)	(4.37)

Table 12

Fama-Macbeth regressions with both investor attention and illiquidity included as interaction variables

Monthly excess returns (Panel A) and 6-month cumulative excess returns (Panel B) are each regressed on the Amihud's illiquidity (ILLIQ), the investor attention variable, the liquidity shock (LIQU), and the interactions between ILLIQ and LIQU and between the attention variable and LIQU using the Fama-MacBeth (1973) methodology. The investor attention variables are the natural logarithm of market capitalization (LNME), the number of analysts covering the firms (CVRG), and the quarterly aggregate institutional holdings (INST). We control for a large set of cross-sectional predictors: the investor attention variable (controlled for one at a time), the level of illiquidity (ILLIQ), the market beta (BETA), the natural logarithm of the book-to-market equity ratio (LNBM), the momentum return (MOM), the short-term reversal (REV), the co-skewness (COSKEW), the idiosyncratic volatility (IVOL), the maximum daily return in a month (MAX), the analyst earnings forecast dispersion (DISP), the Pastor and Stambaugh liquidity beta (PS), the standard deviation of TURN (SDTURN), and the coefficient of variation in the Amihud's illiquidity measure (CVILLIQ). For brevity, we suppress the average coefficients of the control variables. They are available upon request. Newey-West t-statistics are given in parentheses.

Panel A. Predicting one-month ahead returns

	LNME to proxy for investor attention				CVRG to proxy for investor attention				INST to proxy for investor attention			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
LIQU	0.196	0.496	0.188	0.459	0.195	0.440	0.181	0.404	0.209	0.442	0.197	0.424
	(7.62)	(6.01)	(7.00)	(5.12)	(7.27)	(7.65)	(6.50)	(6.60)	(6.95)	(5.97)	(6.39)	(5.57)
Attention×LIQU		-0.049		-0.044		-0.134		-0.120		-0.487		-0.461
		(-4.14)		(-3.48)		(-5.27)		(-4.57)		(-3.99)		(-3.82)
ILLIQ×LIQU			0.000	0.066			0.001	0.113			-0.001	0.116
			(0.38)	(1.44)			(0.52)	(2.52)			(-0.52)	(2.55)

Panel B. Predicting 6-month cumulative returns

	LNME to proxy for investor attention				CVRG to proxy for investor attention				INST to proxy for investor attention			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
LIQU	0.315	1.191	0.293	1.092	0.336	1.204	0.290	1.110	0.354	1.013	0.310	0.941
	(4.04)	(3.86)	(3.52)	(3.55)	(4.05)	(6.40)	(3.31)	(6.33)	(3.74)	(4.18)	(3.21)	(3.94)
Attention×LIQU		-0.141		-0.126		-0.465		-0.434		-1.422		-1.293
		(-2.90)		(-2.67)		(-4.99)		(-5.00)		(-3.21)		(-3.09)
ILLIQ×LIQU			0.002	0.210			0.003	0.293			0.002	0.396
			(0.44)	(1.29)			(0.59)	(1.70)			(-0.51)	(1.98)

Table 13
Conditional measure of liquidity shock

The firm's conditional measure of liquidity shock (LIQCU) in month t is computed as the negative of the difference between the realized Amihud's illiquidity (ILLIQ) and the conditional mean of illiquidity (EILLIQ), scaled by the conditional volatility of illiquidity (VILLIQ) in the month. EILLIQ and VILLIQ are jointly estimated under the assumption that conditional mean and volatility of Amihud's illiquidity follow an ARMA(1,1) and GARCH(1,1) processes. Panel A reports the time-series averages of the cross-sectional correlations (multiplied by 100) between the illiquidity variables. SDILLIQM is the standard deviation of daily ILLIQ in a month; MILLIQ and SDILLIQ are the mean and standard deviation of monthly ILLIQ over the past 12 months; LIQU is the liquidity shock measure computed as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation; and SPRDU is the shock to monthly equal-weighted quoted spread (SPRD), multiplied by -1. Panel B reports the average returns in month $t+1$ and the 3-factor Fama and French (1993) alphas for each LIQCU portfolio. Column "Avg. LIQCU" reports average LIQCU values in month t for each decile portfolio. The last column shows the average market share of each portfolio. The last three rows show the differences in monthly returns between High and Low LIQCU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles, and between decile 1 and the rest of deciles. Panel C reports the average slope coefficients from the monthly predictive regressions of excess returns on a set of lagged predictive variables using the Fama-MacBeth methodology. Newey-West t-statistics are given in parentheses.

Panel A. Correlation coefficients

	LIQCU	EILLIQ	VILLIQ	LIQU	ILLIQ	SDILLIQM	SDILLIQ	MILLIQ	SPRD
EILLIQ	-2.6								
VILLIQ	-2.7	90.8							
LIQU	69.8	12.4	6.6						
ILLIQ	-18.8	76.6	68.3	-25.6					
SDILLIQM	-19.3	71.2	64.9	-26.0	96.4				
SDILLIQ	-4.3	76.2	76.9	-6.8	75.3	74.4			
MILLIQ	-4.6	81.3	79.2	-5.9	80.5	78.3	95.9		
SPRD	-16.3	75.9	69.3	-24.8	62.9	57.0	58.5	63.6	
SPRDU	31.7	-9.1	-4.2	50.5	-14.1	-12.2	-3.3	-3.5	-31.4

Table 13 – continued

Panel B: Univariate portfolio sorts

Decile	Avg. RET	Alpha	Avg. LIQCU	Mkt. shr.
1 (Low)	0.74	-0.56	-1.74	7.45%
	(0.93)	(-4.85)		
2	1.03	-0.25	-0.74	10.01%
	(1.96)	(-2.75)		
3	1.18	-0.11	-0.30	10.44%
	(2.48)	(-1.26)		
4	1.24	-0.05	-0.01	9.83%
	(2.69)	(-0.62)		
5	1.33	0.05	0.20	9.54%
	(2.99)	(0.72)		
6	1.42	0.20	0.37	9.33%
	(3.39)	(1.68)		
7	1.42	0.16	0.54	9.30%
	(3.37)	(2.61)		
8	1.45	0.23	0.72	9.97%
	(3.51)	(3.17)		
9	1.42	0.19	0.94	11.15%
	(3.49)	(3.31)		
10 (High)	1.47	0.23	1.39	12.99%
	(3.76)	(2.90)		
High-Low	0.73	0.79		
	(5.98)	(6.29)		
High-the rest	0.23	0.24		
	(3.67)	(3.79)		
Low-the rest	-0.59	-0.63		
	(-6.29)	(-6.77)		

Table 13 – continued

Panel C: Monthly predictive regressions

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
LIQCU	0.305	0.188	0.183	0.196	0.140	0.222	0.184	0.191	0.187	0.186	0.196
	(12.73)	(7.24)	(7.43)	(7.98)	(4.69)	(8.46)	(7.37)	(7.48)	(7.27)	(6.83)	(7.59)
BETA	0.071	0.057	0.120	0.146	0.051	0.061	0.059	0.048	0.054	0.011	0.131
	(0.65)	(0.59)	(1.33)	(1.55)	(0.42)	(0.65)	(0.62)	(0.51)	(0.58)	(0.11)	(1.52)
LNME	-0.137	-0.167	-0.234	-0.232	-0.128	-0.112	-0.108	-0.107	-0.143	-0.154	-0.194
	(-3.09)	(-3.82)	(-6.15)	(-5.74)	(-3.05)	(-2.75)	(-2.73)	(-2.65)	(-3.09)	(-3.54)	(-4.50)
LNBM	0.317	0.307	0.277	0.277	0.212	0.303	0.306	0.304	0.299	0.310	0.256
	(4.48)	(4.44)	(4.21)	(4.14)	(2.42)	(4.34)	(4.39)	(4.39)	(4.35)	(4.34)	(3.88)
MOM	0.007	0.008	0.008	0.007	0.008	0.008	0.008	0.008	0.008	0.007	0.009
	(4.94)	(5.84)	(5.36)	(5.09)	(4.40)	(5.86)	(5.56)	(5.49)	(5.95)	(5.09)	(6.62)
REV	-0.064										
	(-13.44)										
COSKEW		-0.500									
		(-0.80)									
IVOL			-0.201								
			(-5.50)								
MAX				-0.078							
				(-7.88)							
DISP					-0.160						
					(-2.32)						
ILLIQ						0.096					
						(3.44)					
MILLIQ							0.063				
							(3.23)				
SDILLIQ								0.071			
								(2.64)			
CVILLIQ									0.200		
									(3.07)		
PS										0.001	
										(0.77)	
SDTURN											-1.049
											(-5.92)

Table 14

Returns on liquidity shock portfolios after controlling for high volume return premium

Stocks are first sorted into low, normal, and high volume portfolios based on the dollar trading volume (VOLD) on the last but second trading day in a month relative to daily dollar trading volume over the prior 49 trading days; stocks within each VOLD grouping are further sorted into quintiles based on the liquidity shock (LIQU). This table reports the average returns for each of the 3×5 portfolios of VOLD and LIQU, the High$-$Low return differences between High and Low LIQU quintile portfolios within each ILLIQ quintile portfolio, and the corresponding 3-factor alphas. The last column ("Avg. RET") presents average return across the VOLD groupings within each LIQU quintile portfolio. Newey-West t-statistics are given in parentheses.

	Low VOLD	Normal VOLD	High VOLD	Avg. RET
LIQU 1	-0.08	0.60	1.10	0.54
2	0.19	1.08	1.47	0.91
3	0.51	1.28	1.74	1.18
4	0.69	1.54	2.04	1.42
LIQU 5	0.92	1.55	2.15	1.54
High - Low	1.01	0.95	1.05	1.00
	(4.94)	(5.41)	(5.17)	(5.80)
Alpha	1.15	1.10	1.19	1.15
	(5.91)	(6.01)	(5.83)	(6.73)

Table 15

Returns on liquidity shock portfolios after controlling for post earnings announcement drift

Stocks are first sorted into quintile portfolios based on the standardized unexpected earnings (SUE); stocks within each SUE quintile are further sorted into quintiles based on the liquidity shock (LIQU). This table reports the average returns for each of the 5×5 portfolios of SUE and LIQU, the High$-$Low return differences between High and Low LIQU quintile portfolios within each ILLIQ quintile portfolio, and the corresponding 3-factor alphas. The last column ("Avg. RET") presents average return across the SUE quintiles within each LIQU quintile portfolio. Newey-West t-statistics are given in parentheses.

	SUE 1	2	3	4	SUE 5	Avg. RET
LIQU 1	0.33	0.77	1.22	1.27	1.64	1.05
2	0.82	1.17	1.41	1.75	1.89	1.41
3	0.93	1.19	1.55	1.83	2.24	1.55
4	1.04	1.54	1.64	1.98	2.37	1.71
LIQU 5	1.04	1.48	1.82	1.98	2.24	1.71
High - Low	0.72	0.71	0.60	0.72	0.60	0.67
	(3.23)	(3.37)	(2.86)	(2.97)	(2.85)	(3.34)
Alpha	0.91	0.92	0.77	0.85	0.80	0.85
	(4.15)	(4.60)	(3.85)	(3.52)	(4.06)	(4.42)

Table A1
An alternative measure of liquidity shock based on the quoted spread

The firm's unusual spread (SPRDU) in month t is computed as the negative of the difference between the equal-weighted quoted spread (SPRD) in month t and the average SPRD over the past 12 months, scaled by the 12-month SPRD standard deviation. Panel A reports the average monthly returns for each SPRDU decile portfolio. Column "Avg. SPRDU" reports the average SPRDU for each portfolio. The last column shows the average market share of each portfolio. The last three rows show the differences in monthly returns between High and Low SPRDU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles; and between decile 1 and the rest of deciles. Average returns and alphas are defined in monthly percentage terms. Panel B reports the average slope coefficients from the monthly predictive regressions of excess returns on a set of predictive variables using the Fama-MacBeth methodology. Newey-West t-statistics are given in parentheses. The sample covers the period from January 1994 to December 2010.

Panel A: Univariate portfolio sorts

Decile	Avg. RET	Alpha	Avg. SPRDU	Mkt. shr.
1 (Low)	0.74	-0.56	-2.42	5.30%
	(0.67)	(-1.84)		
2	0.85	-0.28	-1.20	7.33%
	(1.30)	(-1.35)		
3	0.90	-0.17	-0.63	8.27%
	(1.50)	(-0.93)		
4	1.12	0.00	-0.22	9.25%
	(1.93)	(-0.01)		
5	1.12	0.03	0.11	9.87%
	(2.06)	(0.20)		
6	1.25	0.21	0.41	10.68%
	(2.54)	(1.99)		
7	1.23	0.20	0.69	11.34%
	(2.56)	(2.10)		
8	1.33	0.34	0.98	12.25%
	(2.87)	(3.40)		
9	1.31	0.32	1.33	12.88%
	(2.88)	(3.02)		
10 (High)	1.45	0.46	2.06	12.82%
	(3.12)	(3.20)		
High-Low	0.71	1.02		
	(2.08)	(2.82)		
High-the rest	0.30	0.45		
	(1.64)	(2.65)		
Low-the rest	-0.56	-0.68		
	(-2.15)	(-2.63)		

Table A1 – continued

Panel B: Monthly predictive regressions

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
SPRDU	0.289	0.197	0.172	0.183	0.093	0.200	0.175	0.189	0.199	0.185	0.190
	(8.43)	(5.31)	(4.65)	(5.13)	(2.09)	(5.08)	(4.71)	(5.02)	(5.15)	(5.34)	(5.18)
BETA	0.208	0.213	0.250	0.259	0.153	0.172	0.194	0.187	0.175	0.221	0.246
	(1.35)	(1.49)	(1.91)	(1.91)	(0.99)	(1.27)	(1.41)	(1.36)	(1.32)	(1.48)	(1.99)
LNME	-0.084	-0.103	-0.175	-0.170	-0.091	-0.081	-0.071	-0.069	-0.102	-0.100	-0.122
	(-1.47)	(-1.77)	(-3.95)	(-3.35)	(-1.79)	(-1.35)	(-1.28)	(-1.28)	(-1.49)	(-1.78)	(-2.15)
LNBM	0.263	0.277	0.243	0.242	0.156	0.260	0.267	0.263	0.258	0.255	0.219
	(2.46)	(2.61)	(2.49)	(2.41)	(1.37)	(2.35)	(2.42)	(2.40)	(2.39)	(2.45)	(2.24)
MOM	0.004	0.005	0.004	0.004	0.006	0.005	0.004	0.005	0.005	0.005	0.005
	(1.81)	(2.61)	(2.34)	(2.16)	(2.68)	(2.57)	(2.23)	(2.44)	(2.60)	(2.45)	(2.90)
REV	-0.041										
	(-8.94)										
COSKEW		-0.695									
		(-1.07)									
IVOL			-0.156								
			(-4.18)								
MAX				-0.054							
				(-6.13)							
DISP					-0.131						
					(-3.05)						
ILLIQ						0.050					
						(3.20)					
MILLIQ							0.047				
							(3.68)				
SDILLIQ								0.030			
								(2.54)			
CVILLIQ									0.049		
									(0.50)		
PS										0.000	
										(0.35)	
SDTURN											-0.428
											(-3.48)

Table A2
Screening for price, listing status, stock exchange, and liquidity shock

Columns "Price>= \$5 per share", "Eliminating delisted firms", "NYSE", "NYSE, Price>= \$5 per share", and "Eliminating stocks in LIQU Decile 1" report the average monthly returns in month $t+1$ and the 3-factor Fama and French (1993) alphas for decile portfolios formed based on the liquidity shock (LIQU) in month t using a sample that consists of (i) all stocks with prices no less than \$5 per share; (ii) stocks that are active with the delisting code equal to 100 or missing in month $t+1$; (iii) stocks listed on the NYSE; (iv) stocks listed on NYSE and with prices no less than \$5 per share, and (v) stocks that do not belong to the lowest LIQU decile of the original sample, respectively. The last three rows present the differences in monthly returns between High and Low LIQU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles, and between decile 1 and the rest of deciles. Newey-West t-statistics are given in parentheses. The sample is from August 1963 to December 2010.

	Price>= \$5 per share		Eliminating delisted firms		NYSE		NYSE, Price>= \$5 per share		Eliminating stocks in LIQU Decile 1	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.38	-0.82	0.53	-0.77	0.54	-0.85	0.64	-0.60	0.75	-0.54
	(-0.22)	(-7.74)	(0.25)	(-4.52)	(0.28)	(-5.79)	(0.73)	(-5.42)	(0.95)	(-4.56)
2	0.77	-0.44	0.83	-0.47	0.94	-0.38	0.96	-0.26	0.99	-0.32
	(1.19)	(-5.11)	(1.19)	(-3.99)	(1.74)	(-3.89)	(2.02)	(-2.62)	(1.74)	(-3.41)
3	0.93	-0.28	1.09	-0.22	1.05	-0.26	1.03	-0.21	1.04	-0.25
	(1.84)	(-3.61)	(2.08)	(-2.35)	(2.15)	(-2.50)	(2.29)	(-2.27)	(2.01)	(-2.91)
4	1.02	-0.19	1.10	-0.19	1.13	-0.16	1.07	-0.15	1.16	-0.13
	(2.23)	(-2.58)	(2.20)	(-2.35)	(2.59)	(-1.74)	(2.57)	(-1.81)	(2.39)	(-1.62)
5	1.11	-0.10	1.25	-0.04	1.20	-0.08	1.18	-0.04	1.28	-0.02
	(2.53)	(-1.63)	(2.70)	(-0.44)	(2.98)	(-0.97)	(3.03)	(-0.50)	(2.77)	(-0.21)
6	1.27	0.07	1.33	0.04	1.28	0.01	1.24	0.03	1.40	0.13
	(3.12)	(1.42)	(2.96)	(0.58)	(3.30)	(0.16)	(3.33)	(0.45)	(3.22)	(1.78)
7	1.33	0.16	1.47	0.21	1.42	0.16	1.37	0.16	1.50	0.30
	(3.42)	(3.19)	(3.48)	(2.92)	(3.91)	(2.34)	(3.86)	(2.37)	(3.70)	(2.55)
8	1.52	0.37	1.60	0.36	1.40	0.15	1.35	0.16	1.62	0.39
	(4.16)	(6.71)	(4.01)	(4.88)	(3.87)	(2.36)	(3.83)	(2.44)	(4.15)	(5.35)
9	1.50	0.37	1.62	0.42	1.40	0.22	1.34	0.20	1.59	0.40
	(4.19)	(6.01)	(4.25)	(5.75)	(4.10)	(3.94)	(3.92)	(3.46)	(4.15)	(5.38)
10 (High)	1.49	0.46	1.57	0.47	1.34	0.26	1.33	0.28	1.58	0.49
	(4.48)	(5.63)	(4.37)	(5.07)	(4.25)	(4.19)	(4.33)	(4.53)	(4.50)	(5.12)
High-Low	1.11	1.28	1.04	1.24	0.81	1.12	0.69	0.88	0.83	1.02
	(6.92)	(7.73)	(4.92)	(5.70)	(3.76)	(6.64)	(4.95)	(6.91)	(4.59)	(5.77)
High-the rest	0.40	0.56	0.37	0.54	0.19	0.39	0.20	0.36	0.32	0.49
	(3.96)	(5.59)	(3.16)	(4.82)	(1.87)	(4.80)	(2.46)	(4.99)	(2.85)	(4.68)
Low-the rest	-0.84	-0.87	-0.79	-0.83	-0.70	-0.85	-0.56	-0.62	-0.60	-0.65
	(-9.26)	(-8.83)	(-5.92)	(-5.77)	(-4.80)	(-6.97)	(-6.54)	(-7.08)	(-5.85)	(-6.06)

Table A3
Value-weighted, Price-weighted, and Liquidity-weighted Portfolios

Columns report the value-weighted, price-weighted, and liquidity-weighted average returns in month $t+1$ and the 3-factor Fama-French (1993) alphas for decile portfolios formed based on the liquidity shock (LIQU) in month t using a sample of all stocks trading at NYSE, AMEX, and NASDAQ. The last three rows present the differences in monthly returns between High and Low LIQU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles, and between decile 1 and the rest of deciles. Newey-West t-statistics are given in parentheses. The sample is from August 1963 to December 2010.

	Value-weighted		Price-weighted		Liquidity-weighted	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.51	-0.51	0.44	-0.67	0.35	-0.72
	(0.26)	(-3.39)	(0.00)	(-4.82)	(-0.30)	(-3.78)
2	0.66	-0.32	0.72	-0.40	0.71	-0.30
	(0.86)	(-3.07)	(1.06)	(-3.92)	(0.98)	(-2.62)
3	0.76	-0.17	1.00	-0.12	0.80	-0.17
	(1.42)	(-1.77)	(2.24)	(-1.17)	(1.49)	(-1.66)
4	0.89	0.00	1.02	-0.08	0.86	-0.07
	(2.06)	(-0.05)	(2.34)	(-1.05)	(1.75)	(-0.90)
5	0.92	0.00	1.11	0.02	0.94	-0.03
	(2.28)	(0.04)	(2.87)	(0.22)	(2.10)	(-0.31)
6	0.89	-0.03	1.04	-0.04	0.95	-0.02
	(2.10)	(-0.40)	(2.49)	(-0.55)	(2.10)	(-0.23)
7	1.08	0.18	1.34	0.29	2.42	2.40
	(3.13)	(2.90)	(3.79)	(4.00)	(1.46)	(1.08)
8	0.95	0.04	1.40	0.35	1.02	0.08
	(2.48)	(0.65)	(3.95)	(5.58)	(2.34)	(0.75)
9	0.94	0.07	1.33	0.30	0.89	-0.01
	(2.25)	(0.88)	(3.64)	(3.66)	(1.80)	(-0.11)
10 (High)	1.06	0.26	1.33	0.42	1.14	0.30
	(3.08)	(3.76)	(3.93)	(4.41)	(3.24)	(3.33)
High-Low	0.55	0.76	0.89	1.08	0.79	1.01
	(3.44)	(4.16)	(5.08)	(5.55)	(3.68)	(4.40)
High-the rest	0.22	0.34	0.29	0.45	0.15	0.17
	(2.50)	(3.82)	(2.75)	(4.05)	(0.74)	(0.58)
Low-the rest	-0.40	-0.51	-0.70	-0.75	-0.73	-0.96
	(-3.34)	(-3.42)	(-6.10)	(-5.50)	(-3.40)	(-3.25)

Table A4
Returns on the liquidity shock portfolios in recessionary vs. expansionary periods

Each month, NYSE, AMEX, and NASDAQ stocks are sorted into ten decile portfolios based on liquidity shock (LIQU), defined as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. This table reports the average monthly returns in month $t+1$ and the 3-factor Fama-French (1993) alphas for each LIQU portfolio. The last three rows show the differences in monthly returns between High and Low LIQU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles, and between decile 1 and the rest of deciles. Average returns and alphas are defined in monthly percentage terms. The non-crisis period sample covers the period from August 1963 to December 2010 and excludes the financial crisis period, July 2007 – June 2009. The expansion and recession periods are based on the NBER business cycle periods. Newey-West t-statistics are given in parentheses.

	Non-crisis periods		Expansion periods		Recession periods	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.47	-0.93	0.55	-0.97	-0.72	-0.44
	(0.05)	(-5.20)	(0.40)	(-5.13)	(-1.00)	(-1.00)
2	0.87	-0.54	0.99	-0.53	-0.53	-0.25
	(1.38)	(-4.40)	(2.04)	(-4.21)	(-0.89)	(-0.71)
3	1.14	-0.29	1.25	-0.29	-0.10	0.10
	(2.36)	(-3.15)	(3.06)	(-2.94)	(-0.56)	(0.31)
4	1.16	-0.26	1.26	-0.24	-0.04	0.09
	(2.51)	(-3.29)	(3.24)	(-3.07)	(-0.53)	(0.32)
5	1.32	-0.11	1.43	-0.10	0.08	0.23
	(3.09)	(-1.44)	(3.87)	(-1.31)	(-0.42)	(0.73)
6	1.40	-0.03	1.50	-0.03	0.23	0.35
	(3.31)	(-0.42)	(4.02)	(-0.47)	(-0.29)	(1.44)
7	1.63	0.28	1.74	0.32	0.20	0.25
	(4.24)	(2.29)	(5.06)	(2.03)	(-0.34)	(1.21)
8	1.72	0.33	1.80	0.30	0.45	0.53
	(4.56)	(4.78)	(5.28)	(3.98)	(-0.10)	(2.97)
9	1.73	0.38	1.84	0.38	0.33	0.39
	(4.79)	(5.00)	(5.73)	(4.68)	(-0.22)	(2.17)
10 (High)	1.69	0.45	1.77	0.42	0.53	0.64
	(4.98)	(4.48)	(5.82)	(3.93)	(-0.02)	(3.02)
High-Low	1.22	1.39	1.23	1.39	1.25	1.08
	(6.02)	(5.72)	(5.55)	(5.50)	(2.13)	(2.14)
High-the rest	0.42	0.58	0.40	0.55	0.54	0.50
	(3.81)	(4.64)	(3.35)	(4.26)	(1.59)	(1.69)
Low-the rest	-0.94	-0.96	-0.96	-0.99	-0.85	-0.70
	(-7.17)	(-6.00)	(-6.78)	(-5.87)	(-2.40)	(-2.22)

Table A5
Subsample Analysis

Each month, NYSE, AMEX, and NASDAQ stocks are sorted into ten decile portfolios based on liquidity shock (LIQU), defined as the negative Amihud's (2002) illiquidity measure, demeaned (using the past 12-month illiquidity as the mean) and divided by its past 12-month standard deviation. This table reports the average monthly returns in month $t+1$ and the 3-factor Fama and French (1993) alphas for each LIQU portfolio. The last three rows show the differences in monthly returns between High and Low LIQU decile portfolios, the corresponding 3-factor alphas, and the differences in returns and alphas between decile 10 and the rest of the deciles, and between decile 1 and the rest of deciles. Average returns and alphas are defined in monthly percentage terms. The results are reported for five decades in our sample: August 1963 – July 1973, August 1973 – July 1983, August 1983 – July 1993, August 1993 – July 2003, and August 2003 – December 2010. Newey-West t-statistics are given in parentheses.

	08/1963–07/1973		08/1973–07/1983		08/1983–07/1993		08/1993–07/2003		08/2003–12/2010	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.03	-0.94	1.36	-0.72	-0.17	-1.21	0.17	-1.01	0.35	-0.76
	(-0.49)	(-6.45)	(0.97)	(-3.48)	(-1.03)	(-5.15)	(-0.22)	(-1.66)	(0.17)	(-1.86)
2	0.45	-0.56	1.62	-0.33	0.44	-0.63	0.47	-0.74	0.77	-0.33
	(0.08)	(-4.36)	(1.37)	(-2.15)	(-0.16)	(-4.21)	(0.18)	(-1.83)	(0.61)	(-1.07)
3	0.82	-0.18	1.76	-0.29	0.62	-0.40	0.92	-0.30	1.05	-0.05
	(0.64)	(-1.71)	(1.52)	(-1.84)	(0.14)	(-3.09)	(0.95)	(-1.08)	(0.96)	(-0.19)
4	0.82	-0.20	1.81	-0.24	0.70	-0.35	0.98	-0.14	0.95	-0.12
	(0.65)	(-2.29)	(1.64)	(-1.72)	(0.29)	(-2.76)	(1.13)	(-0.61)	(0.89)	(-0.52)
5	1.02	0.00	1.84	-0.22	0.78	-0.22	1.20	0.07	1.23	0.15
	(0.95)	(0.00)	(1.73)	(-1.79)	(0.45)	(-1.59)	(1.56)	(0.33)	(1.16)	(0.56)
6	1.25	0.20	2.00	-0.02	0.88	-0.17	1.22	0.09	1.11	0.07
	(1.26)	(2.27)	(1.97)	(-0.17)	(0.58)	(-1.03)	(1.55)	(0.50)	(1.10)	(0.31)
7	1.38	0.34	2.13	0.06	1.29	0.51	1.46	0.35	1.15	0.17
	(1.49)	(3.22)	(2.22)	(0.49)	(1.52)	(1.29)	(1.83)	(1.63)	(1.21)	(0.89)
8	1.32	0.28	2.24	0.22	1.19	0.16	1.87	0.80	1.20	0.25
	(1.42)	(3.15)	(2.37)	(1.79)	(1.19)	(1.05)	(2.68)	(4.33)	(1.33)	(1.33)
9	1.25	0.26	2.21	0.25	1.22	0.15	2.02	0.95	1.22	0.32
	(1.37)	(2.23)	(2.41)	(2.16)	(1.28)	(1.37)	(3.00)	(4.46)	(1.44)	(2.64)
10 (High)	1.31	0.41	2.11	0.33	1.32	0.28	2.00	1.01	1.00	0.23
	(1.62)	(2.72)	(2.38)	(2.09)	(1.58)	(2.22)	(2.97)	(3.56)	(1.28)	(1.54)
High-Low	1.27	1.35	0.75	1.05	1.49	1.49	1.83	2.03	0.65	0.98
	(4.15)	(5.41)	(2.80)	(3.32)	(4.92)	(6.75)	(2.52)	(2.63)	(1.18)	(2.19)
High-the rest	0.38	0.50	0.23	0.47	0.54	0.52	0.86	1.00	-0.01	0.26
	(1.89)	(3.07)	(1.37)	(2.53)	(3.82)	(4.28)	(2.38)	(2.85)	(-0.02)	(1.03)
Low-the rest	-1.04	-1.00	-0.61	-0.69	-1.11	-1.14	-1.18	-1.25	-0.73	-0.83
	(-5.68)	(-6.61)	(-3.60)	(-3.52)	(-5.04)	(-6.50)	(-2.46)	(-2.32)	(-2.41)	(-3.04)