Liquidity Shocks and Stock Market Reactions

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We find that the stock market underreacts to stock-level liquidity shocks: liquidity shocks are not only positively associated with contemporaneous returns, but they also predict future return continuations for up to six months. Long-short portfolios sorted on liquidity shocks generate significant returns of 0.70% to 1.20% per month that are robust across alternative shock measures and after controlling for risk factors and stock characteristics. Furthermore, we show that investor inattention and illiquidity contribute to the underreaction: while both are significant in explaining short-term return predictability of liquidity shocks, the inattention-based mechanism is more powerful for the longer-term return predictability. (*JEL* G02, G10, G11, G12, G14, C13)

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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. Amihud and Mendelson (1986) were the first to argue that investors demand a premium for less liquid stocks, so that less liquid stocks should have higher average returns. Subsequently, it is well documented that the level of individual stock illiquidity is positively priced in the cross-section of expected stock returns.[1]

Liquidity is also time-varying, and subject to shocks that have persistent effects (that is, negative liquidity shocks predict lower future liquidity). 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 positive relation between stock-level illiquidity and expected returns, a persistent negative shock to a security's liquidity should, as pointed out by Acharya and Pedersen (2005), result in low contemporaneous returns and high future returns, and vice versa. However, this prediction of a negative relation between liquidity shocks and future returns may not hold in a market in which information is not fully reflected into prices due to market frictions. Thus, studying market reactions to liquidity shocks can generate important insights on how the market processes information about liquidity shocks and on the information efficiency of financial markets.

There are two potential market frictions that prevent public information from being incorporated in security prices: 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 stock fundamentals, such as new products, earnings news, demographic information, innovative efficiency, or information about related stocks.[2]

This paper focuses on liquidity shocks, which can be viewed as a type of public information on liquidity. Compared with the direct and well defined information events studied in the previous literature, liquidity shocks are not well defined and their pricing implications are harder to interpret by average investors. As argued by Hirshleifer, Hsu, and Li (2013), investors would "have greater difficulty processing information that is less tangible"; the indirect and ellusive nature of liquidity news thus makes the investors' attention constraints more likely to be binding. As a result, the stock market can underreact to liquidity shocks. Moreover, as indicated in the model of Peng and Xiong (2006), an investor who optimizes the amount of attention allocation would

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

[2] See, for example, Huberman and Regev (2001), Hirshleifer et al. (2004), Hou and Moskowitz (2005), Hirshleifer, Lim, and Teoh (2009), Hong, Torous, and Valkanov (2007), DellaVigna and Pollett (2007, 2009), Barber and Odean (2008), Cohen and Frazzini (2008), and Hirshleifer, Hsu, and Li (2013).

allocate more attention to systematic shocks and less to stock-specific shocks (in some cases even completely ignoring them). Thus, a strong case can be made for underreaction to stock-level liquidity shocks based on theories of investor attention. Alternatively, when a stock is harder to trade due to its illiquidity, price discovery can be delayed, resulting in slow price adjustments following liquidity shocks.

To investigate how the stock market reacts to stock-level liquidity shocks, we first examine the immediate effect of liquidity shocks and find that it is positive and significantly related to contemporaneous stock returns. However, in terms of the relation between liquidity shocks and future returns, contrary to the negative relation as one would expect in a full, informationally efficient setting, we find the relation continues to be positive and highly significant. Depending on the proxy for liquidity shock, decile portfolios that are long in stocks with positive liquidity shocks and short in stocks with negative liquidity shocks generate one-month-ahead raw and risk-adjusted returns of 0.75% to 1.23% per month for equal-weighted portfolios, and 0.67% to 1.17% for value-weighted portfolios. The predictive power of liquidity shocks on future returns remains economically and statistically significant for up to six months.

This evidence suggests that the market underreacts to stock-level liquidity shocks. Although negative and persistent liquidity shocks do result in decreases in stock prices due to a higher future risk premium, the price adjustment is not complete within the same month. As a result, there is a considerable amount of continuation of negative returns, and the effects of shocks are not fully incorporated into prices until months later. The opposite is true for positive liquidity shocks.

We further investigate the underlying mechanisms that may contribute to the underreaction to liquidity shocks. The investor attention theory predicts that the degree of underreaction to liquidity shocks, as measured by its return predictability, should be more pronounced for stocks that receive less investor attention. In contrast, 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 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 return predictability of liquidity shocks. While both mechanisms are significant for one-month-ahead return prediction, the inattention-based mechanism is more powerful in predicting two- to four-month-ahead returns. Our results thus suggest that both investor inattention and illiquidity can drive stock market underreactions to liquidity shocks, but investor attention is a more dominant factor than illiquidity.

Our results are based on three measures of liquidity shocks. The first is the negative difference between Amihud's (2002) illiquidity measure and its past 12-month average.[3] In addition to this simple, nonparametric measure, we use a parametric methodology to construct a conditional measure of liquidity shocks using an ARMA(1,1) specification for Amihud illiquidity.

It could be argued that innovations in the Amihud illiquidity measure may capture quote changes upon the arrival of public news—that is, the market makers update prices upon news without much trading—rather than real changes in liquidity. To account for this possibility and ensure that our results are robust, we also use an alternative measure of liquidity shocks based on the changes in bid-ask spreads. The results are similar to those from the changes in the Amihud illiquidity measure.

In addition to the univariate portfolio-level analyses, we examine double-sorted portfolios and perform stock-level Fama-MacBeth regressions to confirm that the relation between liquidity shocks and future returns is robust by employing an extensive list of control variables. Liquidity shocks can be correlated with several liquidity-related factors that are known to be related to expected returns. Earlier studies show that the stock-level illiquidity and systematic liquidity risk are important determinants of expected stock returns. Hence, we control for the level of illiquidity as well as exposures to systematic liquidity risks 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 relation. Our results remain significant after controlling for the volatility of liquidity.

We control for other risk factors and stock characteristics that have been shown to predict 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 and colleagues 2006, 2009) and its changes, and preference for lottery-like assets (Bali, Cakici, and Whitelaw 2011). After controlling for a large set of stock return predictors, the

[3] The Amihud measure of stock-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's 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 measure has the highest correlation with the price impact coefficient computed with data on intraday transactions and quotes.

positive relation between liquidity shocks and future returns remains highly significant.

Furthermore, this economically and statistically significant relation between liquidity shocks and future returns is robust to microstructure effects and across various subsamples, including expansionary and recessionary periods as well as the five decades in our sample. The results also hold when we use different portfolio-weighting schemes, and when we restrict the sample to NYSE/AMEX, NYSE, and S&P 500 stocks.

Given that liquidity is endogenous, it is possible that the return predictability of liquidity shocks picks up the market's underreaction to other news or mechanisms that coincide with liquidity changes. While a comprehensive exploration of the source of liquidity shocks is beyond the scope of this paper, we attempt to control for three specific sources that have the potential to affect liquidity.

First, as shown by Beaver (1968), Ball and Brown (1968), and Bernard and Thomas (1989, 1990), a stock's earnings announcements can lead to both future return predictability and changes in trading volume. As changes in volume can be associated with liquidity changes, we control for the information contained in earnings announcements and find that the return predictability of liquidity shocks is still statistically and economically significant.

Second, changes in trading volume may be driving the significant effect of liquidity shocks. As shown by Gervais, Kaniel, and Mingelgrin (2001), stocks experiencing abnormally high (low) trading volume over a day or a week also tend to have high (low) abnormal returns in the following month. To ensure that the effect of liquidity shocks is not driven by unexpected trading volume, we follow Gervais, Kaniel, and Mingelgrin (2001) and classify stocks into low-, normal-, and high-volume portfolios based on volume changes and define dummy variables based on the portfolio that a stock belongs to. We further construct a continuous volume shock variable in the same fashion as our liquidity shock variable. Our results remain robust after controlling for both measures of volume shocks, suggesting that the return predictability of liquidity shocks is distinct from the abnormal volume effect.

Third, changes in volatility may contribute to changes in liquidity, especially in the case where liquidity is measured as a function of volatility. Since our main findings survive volume controls, the remaining issue is whether investors are just underreacting to volatility shocks. We construct a volatility shock variable based on idosyncratic volatility and control for it in both the bivariate portfolio-level analysis and Fama-MacBeth regressions. Our results show that the predictive power of liquidity shocks remains intact.[4]

[4] We also obtain similar results when volatility shock is defined as changes in absolute returns. However, it should be noted that volatility is unobservable, and thus it is possible that these conventional measures of volatility shocks (based on either idosyncratic volatility or absolute returns) do not fully capture the true underlying volatility changes. As a result, underreaction to volatility changes may still be partially responsible for the observed underreaction to liquidity shocks.

Generally speaking, if markets are rational and react to information promptly, 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. It is possible that our results can be explained by investors' underreaction to some other variable that is correlated with liquidity (such as volatility). Nevertheless, our findings remain significant after controlling for past returns and past earnings surprises, as well as an extensive list of other factors, suggesting that the return predictability of liquidity shocks is a new finding that can not be explained by mechanisms proposed in the existing literature.

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 theory of investor inattention is important in understanding stock market underreactions 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 underreaction to stock-level liquidity shocks. The results suggest that liquidity shocks and how the stock market reacts are important in predicting the cross-section of future stock returns.

1. Data

Our sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ exchanges, covering the period from July 1963 through December 2010. We eliminate stocks with price per share less than \$5 or more than \$1,000. 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) data for the period of 1993–2010. The institutional ownership data are from Thompson 13F filings for the period of 1980–2010.

1.1 Measures of liquidity and liquidity shocks

Following Amihud (2002), we measure the illiquidity of 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:

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

[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%.

where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock i on day d, respectively.[6] A stock is required to have at least 15 daily return observations in month t. The Amihud illiquidity measure is scaled by 10^6.

We first use a parsimonious model for liquidity shock (denoted LIQU), defined as the negative difference between ILLIQ and its past 12-month average:

$$LIQU_{i,t} = -\left(ILLIQ_{i,t} - AVGILLIQ_{i|t-12,t-1}\right), \tag{2}$$

where $AVGILLIQ_{i|t-12,t-1}$ is the mean of illiquidity over the past 12 months. Positive (negative) liquidity shocks indicate an increase (decrease) in liquidity relative to its past 12-month average.

We also adopt a parametric methodology to generate a conditional measure of liquidity shocks (denoted LIQCU). The Amihud illiquidity measure of stock i is assumed to follow an ARMA(1,1) process:

$$ILLIQ_{i,t} = \alpha_{0,i} + \alpha_{1,i} ILLIQ_{i,t-1} + \alpha_{2,i}\varepsilon_{i,t-1} + \varepsilon_{i,t}, \tag{3}$$

where $\varepsilon_{i,t}$ is normally distributed with a time-invariant standard deviation.[7] The parameters are estimated via the maximum likelihood method using a 60-month rolling sample that requires a minimum of 24 observations and is updated on a monthly basis. We define LIQCU as the negative difference between the realized ILLIQ of stock i and its conditional mean estimated from the ARMA(1,1) model in month t, $-\varepsilon_{i,t}$ in Equation (3).[8]

We further adopt an alternative measure of liquidity based on the volume-weighted effective relative spread (SPRD).[9] Spreads are calculated using Trade and Quotes (TAQ) data covering the period of 1993–2010. We obtain National Best Bid and Offer (NBBO) following Hasbrouck's procedure.[10] We apply several filters to delete invalid trades and quotes. We delete trades if price is negative or zero or trading volume is negative or zero; if the correction indicator

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6 Following Gao and Ritter (2010), we adjust for institutional features of the way that NASDAQ and NYSE/AMEX volume are counted. Specifically, we divide NASDAQ volume by 2.0, 1.8, 1.6, and 1 for the periods prior to February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and January 2004 and later years, respectively.

7 We used the Akaike information criterion (AIC) and Schwarz Bayesian criterion (SBC) to determine the optimal lag length for ARMA specification. Since the improvement in terms of AIC and SBC is minimal when we use larger number of lags, we decided to use the most parsimonious model in Equation (3). Moreover, the results from alternative specifications of the ARMA model are similar to those based on the ARMA(1,1) specification.

8 At an earlier stage of the study, we construct standardized measure of liquidity shocks defined as the demeaned liquidity scaled by the standard deviation of liquidity. We estimate the mean and standard deviation of liquidity using the past 12-month liquidity values. Alternatively, we model liquidity using a ARMA(1,1)–GARCH(1,1) model in which the conditional mean and conditional volatility of liquidity are used to construct standardized liquidity shocks. The results from the two alternative liquidity shock measures are very similar to those reported in our tables, and are available upon request.

9 Our findings are robust to alternative spread measures, such as the quoted bid-ask spread and the equal-weighted effective spread.

10 See http://people.stern.nyu.edu/jhasbrou.

is not 0 (no correction) or 1 (contain corrected value); if the sale condition is not blank, "∗," "@," or "E"; if they are the first trade of the day; and if price is greater than 1.5 or less than 0.5 times the lagged price. We delete quotes if quote condition is not 3 (closing), 10 (opening), or 12 (regular); if bid (denoted bid) is less than or equal to zero; if bid is greater than or equal to offer (denoted *ofr*); and if $ofr - bid > 0.5 \times bid$. In matching trade and quote files, for data prior to 1999 we follow the five-second lag rule proposed by Lee and Ready (1991), and for data in 1999 and later years, we follow Bessembinder and Venkataraman (2010) and do not apply time lag. The volume-weighted effective relative spread is scaled by 10^2.

We construct the stock's negative spread shock (SPRDU) as:

$$SPRDU_{i,t} = -(SPRD_{i,t} - AVGSPRD_{i|t-12,t-1}), \qquad (4)$$

where $AVGSPRD_{i|t-12,t-1}$ is the mean of SPRD over the past 12 months. A positive (negative) $SPRDU$ is associated with decrease (increase) in effective spread relative to its past 12-month average, and hence, increase (decrease) in liquidity.

1.2 Control variables

We employ a large set of control variables in our tests. Unless otherwise stated, all variables are measured as of the end of portfolio formation month (that is, month t) and require a minimum of 15 daily observations for all variables computed from daily data.[11]

Following Fama and French (1992), we estimate the market beta of individual stocks using monthly returns over the prior 60 months if available (or a minimum of 24 months). The stock'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, 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. The stock's monthly co-skewness (COSKEW) is constructed as in Harvey and Siddique (2000) using the monthly return observations over the prior 60 months (if at

11 A detailed description of the control variables is provided in the Appendix.

least 24 months are available). The monthly idiosyncratic volatility of stock i (IVOL) is computed as in Ang et al. (2006). The stock's extreme positive return (MAX) is defined as its maximum daily return in a month following Bali, Cakici, and Whitelaw (2011). 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.

It is possible that liquidity shocks may coincide with earnings shocks, and it is well known that earnings shocks are followed by a post-earnings-announcement drift. To control for this effect, we follow Ball and Brown (1968) and Bernard and Thomas (1989, 1990), and construct standardized unexpected earnings (SUE), defined as changes in earnings from four quarters ago, standardized by its standard deviation over the past eight quarters (with a minimum of four UE observations available).[12]

Since a stock's liquidity and trading volume are positively related, there is a concern that our liquidity shock variable may be capturing the high-volume return premium effect documented by Gervais, Kaniel, and Mingelgrin (2001). To control for the high-volume return premium, we follow Gervais, Kaniel, and Mingelgrin (2001) and classify stocks into low-, normal-, and high-volume portfolios. If the dollar trading volume on the one-day formation period is among the highest (lowest) 10% of the daily dollar trading volume over the prior 49 trading days, the stock is classified as a high- (low-) volume stock, otherwise the stock is classified as normal-volume stock. We then create two dummy variables: the high-volume dummy variable (GKM_H) is 1 if a stock belongs to the high-volume group and zero otherwise; the low-volume dummy variable (GKM_L) equals 1 if a stock resides in the low-volume portfolio and zero otherwise. In addition to the GKM variables, we further control for volume changes by constructing a continuous variable for abnormal dollar volume (VOLDU) in the same fashion as we define the liquidity shock. That is, we subtract its past 12-month average from monthly dollar volume.

We also control for a wide variety of liquidity-based variables. Following Chordia, Subrahmanyam, and Anshuman (2001), the standard deviation of turnover (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 illiquidity measure in a month scaled by the monthly Amihud illiquidity measure.

Following Pastor and Stambaugh (2003), we estimate the stock's liquidity exposure (PS) to innovations in the aggregate liquidity factor.[13] To capture covariances of a stock's own return and liquidity with the market return and

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12 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 variables.

13 Innovations in aggregate liquidity factor are downloaded from Lubos Pastor's website.

market liquidity, we follow Acharya and Pedersen (2005) and estimate the four betas. BETA1 is the market beta, BETA2 corresponds to the covariation of a stock's liquidity with the market liquidity, BETA3 captures the covariation between a stock's return and market liquidity, and BETA4 captures the covariation between a stock's liquidity and market returns. More specifically, each month, we classify common stocks listed on NYSE, AMEX, and NASDAQ into 25 test portfolios sorted on the average daily Amihud illiquidity over the previous year using NYSE breakpoints. We then normalize the Amihud illiquidity measure as suggested by Acharya and Pedersen (2005) and estimate the monthly innovations of illiquidity for the market and the test portfolios by extracting the residuals from an AR(2) model using a 60-month rolling window with at least 24 monthly observations. Using these illiquidity innovations and returns, we estimate the liquidity betas for testing portfolios and assign the betas of the illiquidity portfolio to stocks that compose it.

We further control for a stock's exposure to the fixed and variable components of the Sadka (2006) liquidity factor.[14] For each month, a stock's illiquidity risk loadings on the fixed and the variable components (denoted SADKAF and SADKAV, respectively) are estimated using monthly return data over the prior 60 months with a minimum of 24 monthly observations available after controlling for the monthly market, size, and book-to-market factors.

Finally, in Section 3, we investigate the pricing effect associated with liquidity shocks in conjunction with alternative measures of investor attention. We use several measures to capture the degree of investor attention: (i) stock size (LNME); (ii) analyst coverage (CVRG), computed as the natural logarithm of the number of analysts covering the stock in the portfolio formation month; and (iii) institutional holdings (INST), defined as quarterly fractional institutional ownership as of the portfolio formation month.[15]

1.3 Summary statistics

We first examine the time-series properties of stock-level illiquidity measures and find that the ILLIQ and SPRD variables are highly autocorrelated with an average AR(1) coefficient of 0.69 and 0.74 across all stocks over the full sample period. The autocorrelation coefficients are consistent with evidence established in the previous literature that shocks to liquidity have persistent effects: a negative liquidity shock leads to lower levels of future liquidity, and vice versa.

Panel A of Table 1 provides the time-series averages of the cross-sectional descriptive statistics for the aforementioned variables. Consistent with improved stock liquidity over time, the mean and median of the alternative

[14] We download the time-series of the monthly fixed and variable components of the illiquidity factor covering the period of April 1984 to December 2010 from Ronnie Sadka's webpage.

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

measures of liquidity shocks are positive over our sample period. Liquidity shocks also show substantial cross-sectional variation with an average standard deviation in the range of 4 (when liquidity shock is measured by SPRDU), 8 (when measured by LIQU), and 12 (when measured by LIQCU) times the corresponding mean.

Panel B of Table 1 reports the time-series averages of the cross-sectional correlation coefficients for the variables. Panel B reveals that the alternative measures of liquidity shocks are highly correlated with an average correlation coefficient ranging from 21% (between SPRDU and LIQCU), to 43% (between LIQU and SPRDU) and 53% (between LIQU and LIQCU). The average correlation coefficients between the contemporaneous stock return (REV) and LIQU, SPRDU, and LIQCU are, respectively, 13%, 12%, and 11%, and highly significant. This is consistent with the hypothesis that liquidity is priced—a positive and persistent liquidity shock reduces future risk premium and increases the contemporaneous stock price. However, Panel B provides preliminary evidence that the market continues to react to liquidity shocks in the future months: the average correlation coefficient between liquidity shocks,

Table 1
Descriptive statistics

Panel A: Summary statistics

Variable	Mean	Median	Std. dev.
RET	1.12	0.51	11.08
ILLIQ	0.81	0.15	2.94
SPRD	0.99	0.70	0.98
LIQU	0.17	0.01	1.39
SPRDU	0.27	0.07	1.02
LIQCU	0.26	0.01	3.07
BETA	1.32	1.21	0.79
LNME	5.34	5.17	1.63
LNBM	−0.50	−0.41	0.74
MOM	20.18	10.92	53.19
REV	1.77	0.79	11.74
COSKEW	−0.01	−0.01	0.08
IVOL	2.12	1.85	1.25
MAX	5.73	4.66	4.50
DISP	0.13	0.02	0.90
SUE	−0.02	−0.01	1.04
GKM_H	0.11	0.03	0.27
GKM_L	0.08	0.00	0.27
VOLDU	0.43	−0.08	3.03
CVILLIQ	1.14	1.03	0.44
SDTURN	0.42	0.24	0.73
PS	−1.20	−0.82	36.10
BETA1	0.93	0.83	1.62
BETA2	0.01	0.00	0.14
BETA3	−0.03	−0.03	0.89
BETA4	−0.02	0.00	0.28
SADKAF	2.44	0.71	35.61
SADKAV	−0.25	−0.15	6.16
CVRG	1.89	1.89	0.77
INST	0.43	0.44	0.24

(continued)

Table 1
Continued

Panel B: Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)
ILLIQ	(2)	0.2																												
SPRD	(3)	0.1	53.4																											
LIQU	(4)	2.4	−19.3	15.4																										
SPRDU	(5)	2.0	−6.4	−15.9	42.8																									
LIQCU	(6)	1.7	−15.3	10.0	52.8	21.4																								
BETA	(7)	−0.9	4.0	3.9	3.4	7.5	6.6																							
LNME	(8)	−0.6	−40.8	−65.3	−12.6	−11.6	−12.5	−22.1																						
LNBM	(9)	2.6	13.4	14.2	3.5	−1.4	−0.9	−13.0	−22.5																					
MOM	(10)	3.5	−7.8	−6.2	22.5	27.0	13.8	5.1	2.5	−14.1																				
REV	(11)	−3.0	−0.5	2.1	12.6	11.9	9.9	1.7	0.1	2.0	0.4																			
COSKEW	(12)	−0.2	−4.1	−10.3	−1.7	−2.2	−2.4	3.7	10.2	4.2	−1.1	0.2																		
IVOL	(13)	−3.7	25.3	39.9	9.8	6.5	12.1	34.2	−41.0	−6.0	1.8	21.2	−4.2																	
MAX	(14)	−3.6	16.2	26.6	11.6	8.3	12.2	28.8	−28.8	−4.8	1.2	42.0	−2.8	85.8																
DISP	(15)	−1.0	−2.7	−0.1	−2.1	−1.1	−1.7	4.0	1.3	3.3	−5.3	−0.8	0.7	3.8	3.1															
SUE	(16)	3.8	−1.1	−2.4	6.8	7.6	1.8	−0.5	3.0	−0.6	23.1	8.5	0.3	−1.3	1.3	−2.3														
GKM_H	(17)	0.5	2.6	5.6	−7.3	−11.0	−3.5	−0.3	−5.0	1.1	−20.7	−28.2	−0.2	4.7	−4.6	2.9	−12.8													
GKM_L	(18)	0.2	−0.8	−1.3	2.7	3.1	0.8	−0.8	1.3	−0.7	8.7	−1.1	0.2	−2.7	−2.1	−0.9	3.6	−8.8												
VOLDU	(19)	1.3	−4.8	−1.7	18.9	16.5	11.4	−1.5	1.6	−0.4	14.6	38.8	−0.1	27.0	32.3	−1.6	9.0	−8.4	−0.9											
CVILLIQ	(20)	0.9	29.6	48.1	2.2	5.0	1.9	−4.5	−36.8	13.2	−5.6	3.7	−4.7	4.1	3.1	−3.1	−1.0	0.5	−0.1	5.3										
SDTURN	(21)	−2.2	−4.3	−1.0	6.7	12.8	7.0	27.7	−15.8	−11.1	20.4	3.8	−0.6	32.1	27.6	3.1	−1.3	−0.6	0.3	8.3	−7.8									
PS	(22)	0.4	−0.5	0.8	0.1	0.5	−0.8	−4.6	1.5	2.0	0.0	0.7	−21.0	−3.6	−2.7	−0.5	0.5	0.2	−0.2	0.6	1.9	−4.1								
BETA1	(23)	−1.4	5.6	5.9	4.1	7.7	7.9	76.8	−24.5	−10.4	5.0	1.7	3.4	33.5	27.8	3.3	−0.6	−1.1	−0.3	−1.5	−3.2	26.9	−10.0							
BETA2	(24)	−0.1	26.9	32.4	13.8	10.2	19.6	16.5	−33.2	4.0	7.4	3.7	−3.6	20.9	15.6	−2.4	0.4	−1.5	0.6	2.6	16.2	5.3	−2.7	16.6						
BETA3	(25)	0.8	−2.6	−5.5	−3.1	−4.4	−4.9	−50.4	12.8	8.7	−3.3	0.0	2.7	−17.5	−14.3	−1.7	0.8	−0.3	0.3	1.1	1.0	−13.8	−2.6	−39.9	−15.8					
BETA4	(26)	0.1	−17.4	−20.3	−8.6	−7.6	−12.4	−14.5	24.7	−2.0	−5.5	−2.2	1.3	−14.8	−11.1	1.7	0.0	1.0	−0.4	−1.5	−10.3	−5.2	2.3	−16.6	−44.3	11.1				
SADKAF	(27)	0.4	3.6	6.5	3.7	3.7	2.8	26.2	−6.4	2.1	4.5	1.5	7.1	6.8	5.4	−0.3	0.5	−0.6	0.0	1.2	3.2	3.4	5.9	7.8	5.1	−8.4	−3.8			
SADKAV	(28)	0.4	0.7	0.5	0.4	0.9	−0.3	−3.1	−0.5	1.3	−0.4	1.1	−13.7	−1.3	−1.0	0.0	−0.1	−0.2	−0.1	0.6	2.0	−1.7	18.0	−7.8	0.9	−6.1	−0.4	−22.1		
CVRG	(29)	−0.9	−26.4	−52.3	−8.1	−11.9	−11.6	−12.1	76.5	−12.6	−6.4	−2.9	14.4	−24.9	−17.3	−3.7	0.4	0.5	0.0	−1.0	−33.8	−5.7	−1.3	−14.9	−25.4	10.3	19.2	−3.6	−1.2	
INST	(30)	0.6	−23.7	−49.9	−14.0	−11.7	−11.4	2.9	53.5	−5.5	−3.3	−4.1	13.6	−21.0	−14.8	2.5	1.5	−0.7	0.0	−2.4	−30.1	1.7	0.0	−1.0	−22.2	−0.4	15.9	−5.6	0.2	43.6

Panel A reports the time-series averages of the cross-sectional mean, median, and standard deviation of each variable used in this paper. All the variables, except for RET, the return in month $t+1$, are computed for individual stocks at the end of the portfolio formation month (month t). LIQU denotes the liquidity shock, defined as the negative Amihud (2002) illiquidity measure (ILLIQ), demeaned using the past 12-month ILLIQ as the mean. SPRDU is the shock to the monthly volume-weighted effective relative spread (SPRD), calculated in the same fashion as LIQU. LIQCU denotes the conditional measure of liquidity shock, defined as the negative of the difference between the realized ILLIQ and the conditional mean of ILLIQ in the month estimated under the assumption that the conditional mean of ILLIQ follows an ARMA(1,1) process. 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. SUE is the standardized unexpected earnings. GKM_H and GKM_L denote the high- and low-volume dummy variables. VOLDU is the dollar trading volume shock, calculated in the same fashion as LIQU and SPRDU. SDTURN denotes the standard deviation of the monthly turnover over the past 12 months. CVILLIQ is the coefficient of variation in the Amihud illiquidity measure. PS is the Pastor and Stambaugh (2003) liquidity beta. BETA1–BETA4 are the Acharya and Pedersen (2005) four liquidity betas. SADKAF and SADKAV are the loadings on the fixed and the variable components of the Sadka (2006) liquidity factor. CVRG denotes the natural logarithm of the number of analysts covering the stock. 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 full sample covers the period from August 1963 to December 2010.

proxied by LIQU, SPRDU, and LIQCU, and one-month-ahead stock returns (RET) are, respectively, 2.4%, 2.0%, and 1.7%, all positive and significant at the 1% level. The liquidity shock variables are also highly correlated with many known return predictors, such as illiquidity level (ILLIQ), size (LNME), momentum (MOM), and return volatility (IVOL). LIQU is positively related to VOLDU, but negatively correlated with GKM_H, suggesting that our liquidity shock variable is distinct from the volume change variable analyzed in Gervais, Kaniel, and Mingelgrin (2001). These variables serve as our controls in the following analysis.

2. Cross-Sectional Relation Between Liquidity Shocks and Stock Returns

The significantly positive correlation between liquidity shocks and one-month-ahead stock returns suggests that negative liquidity shocks (reductions in liquidity) are related to lower future stock returns, and vice versa. 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 stock characteristics that are known to predict future stock returns in the cross-section.

2.1 Univariate portfolio-level analysis

We begin our empirical analysis with univariate portfolio sorts. For each month, we sort common stocks trading on NYSE/AMEX/NASDAQ into decile portfolios based on one of the three proxies for liquidity shocks (LIQU, SPRDU, and LIQCU), and compare the performance of high liquidity-shock portfolios to low liquidity-shock portfolios in the contemporaneous and the following months. The NYSE breakpoints are used to alleviate the concern that the CRSP decile breakpoints are distorted by the large number of small NASDAQ and AMEX stocks.[16]

We first examine the effect of liquidity shocks on same-month returns. Table 2 reports the averages of returns, three-factor Fama and French (1993) alphas of each of these LIQU-sorted deciles, as well as portfolio characteristics: liquidity shock (LIQU), monthly illiquidity level (ILLIQ), and market share. The t-statistics are calculated using Newey-West (1987) standard errors and are reported in parentheses. The average liquidity shock (LIQU) increases from −0.90 in Decile 1 to 1.31 in Decile 10, which implies that stocks in the lowest LIQU decile (Decile 1) have negative liquidity shocks (that is, decrease in the level of liquidity), whereas stocks in the highest LIQU decile (Decile 10) have positive liquidity shocks (that is, increase in the level of liquidity).

Table 2 shows a positive relation between LIQU and the same-month returns: the average return for stocks in the highest liquidity shock decile is 4.51%

[16] At an earlier stage of the study, we also used the CRSP breakpoints with equal number of stocks in decile portfolios. The results from univariate and bivariate portfolio sorts based on the CRSP breakpoints are similar to those reported in our tables, and they are available upon request.

Table 2
Contemporaneous returns for portfolios formed on LIQU

	Equal-weighted		Value-weighted				
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. LIQU	Avg. ILLIQ	Mkt. shr.
1 (Low)	−0.39	−1.61	0.04	−1.10	−0.8970	2.6533	4.73%
	(−1.61)	(−12.18)	(0.17)	(−8.20)			
2	−0.25	−1.40	0.30	−0.78	−0.0803	0.2963	10.55%
	(−1.00)	(−12.73)	(1.25)	(−6.87)			
3	0.22	−0.92	0.69	−0.39	−0.0335	0.1479	16.59%
	(0.88)	(−8.93)	(2.85)	(−3.55)			
4	0.61	−0.51	1.12	0.07	−0.0132	0.0881	16.68%
	(2.42)	(−5.17)	(4.51)	(0.64)			
5	0.96	−0.13	1.60	0.60	−0.0006	0.0704	15.22%
	(4.01)	(−1.58)	(6.89)	(8.01)			
6	1.36	0.29	2.12	1.14	0.0111	0.0716	12.56%
	(5.73)	(4.17)	(8.86)	(13.49)			
7	1.74	0.67	2.64	1.66	0.0270	0.0927	9.28%
	(7.27)	(10.14)	(10.38)	(14.34)			
8	2.08	0.99	3.15	2.14	0.0551	0.1415	6.91%
	(8.92)	(13.52)	(12.22)	(16.59)			
9	2.61	1.48	3.80	2.76	0.1209	0.2463	4.66%
	(10.43)	(18.00)	(13.81)	(18.55)			
10 (High)	4.51	3.29	5.27	4.11	1.3128	0.9851	2.84%
	(15.05)	(25.93)	(15.94)	(22.67)			
High–Low	4.90	4.89	5.23	5.20			
	(28.88)	(28.92)	(22.15)	(21.67)			

For month t, NYSE, AMEX, and NASDAQ stocks are sorted into 10 decile portfolios based on their liquidity shock (LIQU) using the NYSE breakpoints. LIQU is defined as the negative Amihud (2002) illiquidity measure (ILLIQ), demeaned using the past 12-month ILLIQ as the mean. This table reports the equal- and value-weighted monthly contemporaneous returns (month t) and the alpha with respect to the Fama-French (1993) factors for each LIQU portfolio. Columns "Avg. LIQU" and "Avg. ILLIQ" report the average LIQU and ILLIQ values for each decile portfolio. The last column shows the average market share of each portfolio. The last row shows the differences in monthly returns between high- and low-LIQU decile portfolios and the alphas. Average returns and alphas are defined in monthly percentage terms. Newey-West t-statistics are given in parentheses. The sample covers the period from August 1963 to December 2010.

for the equal-weighted returns and 5.27% for the value-weighted returns. Those in the lowest liquidity shock decile post an equal-weighted average return of −0.39% and a value-weighted average return of 0.04%. The equal-weighted and value-weighted return differences between the highest and lowest LIQU decile portfolios are, respectively, 4.90% and 5.23%, which are highly significant and cannot be explained by the Fama-French factors.[17] These results indicate that the initial reaction to liquidity shocks is consistent with the findings of positive illiquidity premium in the prior literature: a negative and persistent liquidity shock increases future expected illiquidity and therefore leads to an immediate decrease in the stock price due to a higher liquidity premium.

Table 2 also reports some characteristics of the portfolios sorted by liquidity shocks. As shown in the last two columns, stocks in the extreme deciles (Decile 1 and 10) are relatively smaller and more illiquid compared to stocks in Deciles

[17] In the online Appendix, Panels A and B of Table A1 summarize the contemporaneous relation between liquidity shocks and stock returns revealed by univariate portfolio sorts on the two other liquidity shock measures: SPRDU and LIQCU. The results are qualitatively similar to those based on LIQU. The average contemporaneous return differences between the highest and the lowest liquidity shock portfolios are in the range of 4.42% to 5.26% varying with the liquidity shock proxy and weighting scheme used in the analysis.

2 to 9. More specifically, stocks in Decile 1 (with the lowest liquidity shocks) have an average market share of 4.73% and average illiquidity of 2.65, whereas stocks in Decile 10 (with the highest liquidity shocks) have an average market share of 2.84% and average illiquidity of 0.99. Note that liquidity shocks do not seem to have a monotonic relation with stock size or the level of illiquidity.

Table 3 presents the average one-month-ahead returns on portfolios sorted by liquidity shocks. The first four columns present results with LIQU, based on the changes in the Amihud illiquidity measure, as the measure of a liquidity shock. The equal-weighted (value-weighted) portfolio raw returns increase almost monotonically with liquidity shocks: from 0.51% (0.43%) per month for the lowest LIQU decile to 1.69% (1.60%) per month for the highest LIQU decile. The return differential between Decile 10 and Decile 1 is 1.18% for the equally weighted portfolio and 1.17% for the value-weighted portfolio. The corresponding Fama-French three-factor adjusted returns are 1.23% and 1.17%, respectively. All the return differentials are statistically significant at the 1% level.

Columns 5–8 present results with liquidity shocks measured as shocks in the bid-ask spreads (SPRDU).[18] The equal-weighted (value-weighted) raw return on the SPRDU portfolios increases with SPRDU as well: from 0.50% (0.56%) per month for the lowest SPRDU decile portfolio to 1.42% (1.23%) per month for the highest SPRDU decile portfolio. The equal-weighted (value-weighted) raw return differences and the corresponding alphas are, respectively, 0.92% and 0.98% (0.67% and 0.79%) per month between the high- and low-SPRDU portfolios. These return differentials are strongly statistically significant as well.

Columns 9–12 report results when liquidity measure is based on LIQCU, residuals from the ARMA(1,1) regression with the Amihud illiquidity measure. The equal-weighted (value-weighted) raw return on the LIQCU portfolios increases monotonically: from 0.77% (0.60%) per month for Decile 1 to 1.52% (1.40%) per month for Decile 10. The equal-weighted (value-weighted) raw return differences and the corresponding alphas are, respectively, 0.75% and 0.76% (0.80% and 0.78%) per month between the high- and low-LIQCU portfolios and they are highly significant.

Overall, these results indicate that, regardless of the liquidity shock proxies or the portfolio-weighting scheme that we use, a portfolio that buys stocks in the highest liquidity shock decile and shorts stocks in the lowest liquidity shock decile yields both economically and statistically significant returns ranging between 0.67% and 1.23% in the next month. Combined with the previous result that liquidity shocks are also positively associated with contemporaneous month stock returns, our findings suggest that the stock market underreacts to liquidity shocks and the reaction continues in the following month.

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[18] We should note that SPRDU are calculated based on TAQ data for the period of 1993–2010, while LIQU and LIQCU are calculated from CRSP data from 1963–2010.

Table 3
One-month-ahead returns for portfolios formed on liquidity shocks

	LIQU				SPRDU				LIQCU			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.51	−0.75	0.43	−0.73	0.50	−0.55	0.56	−0.54	0.77	−0.49	0.60	−0.55
	(1.84)	(−8.75)	(1.68)	(−7.45)	(1.42)	(−4.18)	(1.43)	(−2.86)	(2.87)	(−6.84)	(2.43)	(−7.19)
2	0.72	−0.45	0.65	−0.42	0.97	−0.17	0.72	−0.32	0.76	−0.41	0.63	−0.41
	(2.75)	(−5.14)	(2.71)	(−4.53)	(2.71)	(−1.30)	(1.80)	(−2.06)	(3.09)	(−5.59)	(2.79)	(−6.13)
3	0.94	−0.17	0.84	−0.17	1.02	−0.06	0.83	−0.10	1.00	−0.10	0.98	−0.01
	(3.81)	(−1.88)	(3.68)	(−1.94)	(3.00)	(−0.53)	(2.55)	(−0.72)	(4.34)	(−1.27)	(4.67)	(−0.09)
4	1.04	−0.06	1.01	−0.01	0.92	−0.17	0.83	−0.11	1.05	−0.01	0.98	0.03
	(4.41)	(−0.79)	(4.56)	(−0.12)	(2.76)	(−2.08)	(2.65)	(−1.09)	(4.75)	(−0.20)	(4.64)	(0.60)
5	1.08	−0.02	0.99	−0.01	0.94	−0.11	0.82	−0.11	1.08	0.02	0.95	−0.01
	(4.47)	(−0.28)	(4.36)	(−0.21)	(3.09)	(−1.30)	(2.81)	(−1.59)	(4.78)	(0.35)	(4.42)	(−0.12)
6	1.07	−0.02	1.04	0.04	1.04	−0.02	0.88	0.00	1.19	0.09	1.14	0.15
	(4.53)	(−0.39)	(4.84)	(0.82)	(3.37)	(−0.21)	(3.04)	(0.00)	(5.16)	(1.37)	(5.28)	(2.75)
7	1.19	0.10	1.21	0.23	0.98	−0.05	0.87	−0.03	1.23	0.11	1.08	0.10
	(5.17)	(1.74)	(5.45)	(3.63)	(3.27)	(−0.67)	(2.94)	(−0.37)	(5.13)	(1.73)	(4.71)	(1.60)
8	1.23	0.10	1.16	0.15	1.01	−0.02	1.12	0.23	1.30	0.12	1.22	0.17
	(5.04)	(1.71)	(4.97)	(1.96)	(3.35)	(−0.20)	(3.66)	(1.68)	(5.13)	(2.24)	(5.01)	(2.76)
9	1.34	0.18	1.29	0.24	1.19	0.14	1.18	0.23	1.41	0.22	1.30	0.23
	(5.27)	(2.89)	(5.32)	(3.49)	(3.76)	(1.77)	(3.49)	(1.74)	(5.51)	(3.94)	(5.24)	(3.49)
10 (High)	1.69	0.48	1.60	0.45	1.42	0.43	1.23	0.25	1.52	0.27	1.40	0.22
	(6.02)	(6.88)	(6.01)	(6.01)	(4.25)	(4.21)	(3.39)	(1.75)	(5.25)	(4.38)	(4.97)	(3.83)
High–Low	1.18	1.23	1.17	1.17	0.92	0.98	0.67	0.79	0.75	0.76	0.80	0.78
	(10.18)	(10.13)	(8.01)	(7.64)	(5.08)	(5.94)	(2.26)	(2.90)	(7.76)	(8.93)	(5.73)	(6.81)

For month t, NYSE, AMEX, and NASDAQ stocks are sorted into 10 decile portfolios based on one of the three liquidity shock measures (LIQU, SPRDU, and LIQCU) using the NYSE breakpoints. LIQU denotes the liquidity shock, defined as the negative Amihud (2002) illiquidity measure (ILLIQ), demeaned using the past 12-month ILLIQ as the mean. SPRDU is the shock to the monthly volume-weighted effective relative spread (SPRD), calculated in the same fashion as LIQU. LIQCU denotes the conditional measure of liquidity shock, defined as the negative of the difference between the realized ILLIQ and the conditional mean of ILLIQ in the month estimated under the assumption that the conditional mean of ILLIQ follows an ARMA(1,1) process. This table reports the equal- and value-weighted one-month-ahead returns (month $t+1$) and the alpha with respect to the Fama-French (1993) factors for each liquidity shock decile portfolio. The last row shows the differences in monthly returns between high- and low-liquidity shock decile portfolios and the corresponding alphas. Average returns and alphas are defined in monthly percentage terms. Newey-West t-statistics are given in parentheses. The sample period for the results based on LIQU and LIQCU is from August 1963 to December 2010. The results for SPRDU are based on the sample period from January 1993 to December 2010.

2.2 Bivariate portfolio-level analysis

As discussed earlier, liquidity shocks are correlated with many well-known characteristics that forecast cross-sectional stock returns, such as level of illiquidity, past return characteristics (reversal, momentum), co-skewness, idiosyncratic volatility, analyst disagreement, and demand for lottery-like stocks. As such, there is some concern that our liquidity shock proxies may capture effects other than liquidity shocks. We control for these other factors with bivariate sorts in this subsection and Fama-MacBeth regressions in Section 2.4.

We perform bivariate sorts on LIQU in combination with market beta (BETA), size (LNME), book-to-market ratio (LNBM), momentum (MOM), short-term reversal (REV), co-skewness (COSKEW), idiosyncratic volatility (IVOL), extreme positive daily return (MAX), analyst dispersion (DISP), earnings shocks (SUE), a variety of liquidity-based variables including the Amihud illiquidity measure (ILLIQ), coefficient of variation in Amihud illiquidity (CVILLIQ), standard deviation of turnover (SDTURN), liquidity exposure (PS) of Pastor and Stambaugh (2003), liquidity exposures (BETA1 to BETA4) of Acharya and Pedersen (2005), exposures to the fixed and variable components of the Sadka liquidity factor (SADKAF and SADKAV), and two variables for abnormal dollar trading volume (GKM and VOLDU).[19]

Table 4 reports the results of conditional bivariate sorts.[20] Stocks are first sorted into quintile portfolios based on one of the aforementioned control variables except GKM, for which stocks are first sorted into high, medium, and low groups following Gervais, Kaniel, and Mingelgrin (2001), and then into LIQU quintiles within each control variable quintile. We report the returns of the LIQU portfolios, averaged across the control groups to produce quintile portfolios with dispersion in LIQU but with similar levels of the control variable. The predictive power of LIQU remains intact in bivariate portfolios. The average raw return differences, ranging from 0.75% to 1.35% per month, are all significant at the 1% level based on the Newey-West t-statistics. The corresponding alphas are also significantly positive, ranging from 0.85% to 1.36% per month.

Table A2 in the online Appendix reports the full return matrix for the double-sorted portfolios. The return difference and the alpha between the high- and low-LIQU portfolios for each control quintile are all positive and highly significant. In particular, Panel U of Table A2 shows that the return differential for high- and low-LIQU portfolio remains positive and significant at 0.71% per month even for the lowest abnormal volume groups defined as in Gervais, Kaniel, and Mingelgrin (2001), suggesting that the predictive power of liquidity shocks is

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19 Due to space constraints, we report the results of bivariate sorts based on the two alternative liquidity shock measures, SPRDU and LIQCU, in the online Appendix, Table A3. It shows that the effect of liquidity shocks on predicting one-month-ahead returns remains robust after controlling for each of these other factors.

20 Our findings remain intact when independent bivariate sorts are used. The results are available upon request.

Table 4
Bivariate portfolio sorts

Quintile	BETA	SIZE	BM	MOM	REV	COSKEW	IVOL	MAX	DISP	SUE	ILLIQ
1 (Low)	0.63	0.68	0.50	0.73	0.45	0.57	0.74	0.73	0.68	0.87	0.69
2	0.97	0.93	0.98	0.89	0.92	0.93	0.93	0.91	1.02	1.23	0.95
3	1.14	1.19	1.15	1.07	1.10	1.10	1.12	1.12	1.16	1.32	1.16
4	1.38	1.32	1.40	1.34	1.39	1.41	1.40	1.39	1.37	1.54	1.30
5 (High)	1.74	1.43	1.71	1.64	1.79	1.72	1.76	1.84	1.69	1.84	1.51
High–Low	1.12	0.75	1.21	0.91	1.35	1.16	1.02	1.11	1.01	0.96	0.82
	(7.46)	(5.89)	(7.84)	(7.38)	(7.65)	(7.46)	(7.89)	(7.50)	(7.04)	(6.61)	(5.37)
Alpha	1.15	0.85	1.24	0.88	1.36	1.19	1.03	1.13	1.02	0.99	0.85
	(7.09)	(6.38)	(7.72)	(7.96)	(7.77)	(7.55)	(7.06)	(7.15)	(7.59)	(6.84)	(5.43)

Quintile	CVILLIQ	SDTURN	PS	BETA1	BETA2	BETA3	BETA4	SADKAF	SADKAV	GKM	VOLDU
1 (Low)	0.46	0.60	0.56	0.51	0.58	0.45	0.57	0.34	0.35	0.62	0.62
2	0.97	0.96	0.92	0.92	0.89	0.89	0.85	0.92	0.95	0.99	0.87
3	1.12	1.11	1.09	1.04	1.08	1.04	1.04	1.04	1.04	1.10	1.09
4	1.30	1.39	1.32	1.28	1.23	1.30	1.26	1.22	1.21	1.21	1.37
5 (High)	1.66	1.74	1.69	1.61	1.35	1.63	1.40	1.51	1.54	1.66	1.67
High–Low	1.20	1.14	1.13	1.11	0.76	1.18	0.82	1.18	1.19	1.03	1.05
	(7.40)	(7.93)	(7.29)	(7.63)	(6.58)	(7.89)	(6.74)	(7.63)	(7.54)	(7.60)	(7.94)
Alpha	1.22	1.17	1.18	1.18	0.88	1.25	0.91	1.33	1.34	0.99	0.99
	(7.39)	(7.58)	(7.45)	(7.43)	(7.87)	(7.11)	(7.35)	(7.60)	(7.22)	(7.42)	(7.20)

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 Fama-French (1993) alphas after controlling for a given stock characteristic. LIQU is computed as the negative Amihud (2002) illiquidity measure, demeaned using the past 12-month illiquidity as the mean. 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. SUE is the standardized unexpected earnings. CVILLIQ is the coefficient of variation in the Amihud illiquidity measure. SDTURN denotes the standard deviation of the monthly turnover over the past 12 months. PS is the Pastor and Stambaugh (2003) liquidity beta. BETA1–BETA4 are the Acharya and Pedersen (2005) four liquidity betas. SADKAF and SADKAV are the loadings on the fixed and the variable components of the Sadka (2006) liquidity factor. GKM divides the sample into the high, median, and low dollar trading volume groups. VOLDU measures the abnormal dollar trading volume. Newey-West t-statistics are reported in parentheses.

not due to the high-volume return premium effect. Overall, the double-sorted portfolio results confirm that these aforementioned control variables alone fail to subsume the return predictive power of the liquidity shock variables.

2.3 Controlling for volume and volatility shocks

Two of our liquidity shock variables (LIQU and LIQCU) depend on the Amihud illiquidity measure that can be viewed as volatility over volume. Hence, the predictive power of liquidity shocks may potentially be driven by shocks to volume and/or volatility. We investigate this issue based on the conditional bivariate sorts on liquidity shocks after controlling for volume and volatility shocks.

We start our analysis by forming 5×5 bivariate portfolios of liquidity shocks (LIQU) and unexpected shocks to volume (VOLDU). Stocks are first sorted into quintile portfolios based on VOLDU, and then into LIQU quintiles within each VOLDU quintile. Panel A of Table 5 reports average returns on 5×5 VOLDU and LIQU portfolios. In the lowest VOLDU quintile portfolio, average returns on LIQU portfolios increase from 0.45% to 1.27% per month, with an average return difference of 0.82% (t-statistic = 8.10) between low- and high-LIQU portfolios. The corresponding alpha is 0.93% per month with a t-statistic of

Table 5
Bivariate sorts controlling for volume shocks and idiosyncratic volatility shocks

Panel A: Control for VOLDU

LIQU	VOLDU (Low)	VOLDU 2	VOLDU 3	VOLDU 4	VOLDU (High)	Avg. RET
1 (Low)	0.45	0.35	0.61	0.72	0.97	0.62
2	0.42	0.81	0.91	1.03	1.16	0.87
3	0.88	0.94	1.05	1.19	1.39	1.09
4	1.03	1.21	1.36	1.52	1.74	1.37
5 (High)	1.27	1.63	1.66	1.78	1.99	1.67
High–Low	0.82	1.28	1.05	1.07	1.02	1.05
	(8.10)	(10.74)	(7.81)	(7.02)	(5.64)	(7.94)
Alpha	0.93	1.28	0.98	0.90	0.87	0.99
	(9.72)	(10.82)	(7.76)	(7.09)	(6.01)	(7.20)

Panel B: Control for IVOLU

LIQU	IVOLU (Low)	IVOLU 2	IVOLU 3	IVOLU 4	IVOLU (High)	Avg. RET
1 (Low)	0.65	0.70	0.84	0.69	−0.02	0.57
2	1.04	0.94	0.98	0.99	0.49	0.89
3	1.14	1.15	1.11	1.14	0.82	1.07
4	1.64	1.36	1.30	1.38	1.20	1.38
5 (High)	1.96	1.96	1.79	1.76	1.43	1.78
High–Low	1.31	1.26	0.95	1.06	1.45	1.21
	(7.46)	(8.02)	(5.09)	(5.94)	(6.24)	(7.91)
Alpha	1.33	1.27	0.96	1.08	1.49	1.23
	(7.52)	(7.60)	(5.08)	(5.81)	(6.97)	(8.09)

This table reports the average returns in month $t+1$ for each portfolio obtained from conditional bivariate sorts by volume shocks (VOLDU) and LIQU (Panel A), and idosyncratic volatility shocks (IVOLU) and LIQU (Panel B). The last column in each panel reports the average returns for each LIQU portfolio across the five control variable quintiles (VOLDU in Panel A, and IVOLU in Panel B). The last two rows in each panel present the return differences between the highest and the lowest LIQU portfolios within each control quintile and the corresponding alphas with respect to the Fama-French (1993) factors. Newey-West t-statistics are reported in parentheses.

9.72. Similarly, in the highest VOLDU quintile portfolio, average returns on LIQU portfolios increase monotonically from 0.97% to 1.99% per month, with an average return difference of 1.02% (t-statistic = 5.64) between low- and high-LIQU portfolios. The corresponding alpha is also positive, 0.87% per month, and highly significant. A notable point in Panel A of Table 5 is that in almost all VOLDU quintiles, average returns on LIQU quintile portfolios increase monotonically as we move from the lowest to highest LIQU quintile. The last column in Panel A of Table 5 presents returns averaged across the VOLDU quintiles to produce quintile portfolios with dispersion in LIQU but with similar levels of VOLDU. It shows that when moving from the lowest to highest LIQU quintile, the monthly return averaged across the VOLDU quintiles increases from 0.62% to 1.67%, with an average return difference of 1.05% (t-statistic = 7.94). The corresponding alpha has a similar magnitude and is highly significant as well. These results provide evidence that after controlling for unexpected shocks to volume, the predictive power of liquidity shocks remains intact in bivariate portfolios. In the next subsection, we will show that liquidity shocks predict future returns after controlling for VOLDU and all other control variables in Fama-MacBeth regressions.

Since our main findings survive volume controls, one remaining issue is whether investors are just underreacting to volatility shocks. Previous studies have documented a volatility feedback effect, that an increase in volatility requires a higher rate of return from the asset, which leads to a fall in the asset price in the contemporaneous period (see, e.g., French, Schwert, and Stambaugh 1987; Campbell and Hentschel 1992). While the contemporaneous relation is well known, the predictive relation between volatility shocks and future returns at individual stock-level is not.[21] It is possible that the stock market underreacts to volatility shocks, thus volatility shocks are accompanied by lower returns both in the contemporaneous period and in the future.[22] To properly control for volatility shocks, we form 5 $\times$ 5 bivariate portfolios of liquidity shocks (LIQU) and unexpected shocks to idiosyncratic volatility (IVOLU). Similar to our liquidity shock variables defined in Equations (2) and (4), we measure unexpected shocks to idiosyncratic volatility (IVOLU) as:

$$IVOLU_{i,t}=\left(IVOL_{i,t}-AVGIVOL_{i|t-12,t-1}\right), \tag{5}$$

where $AVGIVOL_{i|t-12,t-1}$ is the mean of idiosyncratic volatility over the past 12 months.

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[21] The negative relation between volatility shocks and contemporaneous returns can also be driven by the leverage effect proposed by Black (1976) and Christie (1982)—that is, as asset prices decline, companies' leverage increases and they become riskier, hence volatility also increases (see, e.g., Nelson 1991; Engle and Ng 1993; Bekaert and Wu 2000; Bollerslev, Litvinova, and Tauchen 2006; An et al. Forthcoming). We control for past returns throughout the analysis to account for this effect.

[22] Bali, Scherbina, and Tang (2009) show that stocks that experience a sudden increase in idiosyncratic volatility earn abnormally high contemporaneous returns but significantly underperform otherwise similar stocks in the future.

Once we generate volatility shocks (IVOLU), stocks are first sorted into quintile portfolios based on IVOLU, and then into LIQU quintiles within each IVOLU quintile. Panel B of Table 5 reports average returns on 5 × 5 IVOLU and LIQU portfolios. In the lowest IVOLU quintile portfolio, average returns on LIQU portfolios increase monotonically from 0.65% to 1.96% per month, with an average return difference of 1.31% (t-statistic = 7.46) between low- and high-LIQU portfolios. The corresponding alpha is 1.33% per month with a t-statistic of 7.52. Similarly, in the highest IVOLU quintile portfolio, average returns on LIQU portfolios also increase monotonically from −0.02% to 1.43% per month, with an average return difference of 1.45% (t-statistic = 6.24). The corresponding alpha is 1.49% per month with a t-statistic of 6.97. A notable point in Panel B is that in all IVOLU quintiles, average returns on LIQU quintile portfolios increase monotonically as we move from the lowest to highest LIQU quintile. The last column in Panel B of Table 5 presents returns averaged across the IVOLU quintiles to produce quintile portfolios with dispersion in LIQU but with similar levels of IVOLU. As shown in the last column, when moving from the lowest to highest LIQU quintile, the monthly return averaged across the VOLDU quintiles increases from 0.57% to 1.78%, with an average return difference of 1.21% (t-statistic = 7.91) between low- and high-LIQU portfolios. The corresponding alpha has a similar magnitude and is highly significant as well. These results indicate that after controlling for volatility shocks, the predictive power of liquidity shocks remains intact.[23]

Another potential concern might be the correlation between spread and volatility that may translate into a correlation between shocks to spread and shocks to volatility. Panel B of Table 1 shows that the average cross-sectional correlation between SPRD and IVOL is about 40%. Since the spread is correlated with volatility, it is useful to disentangle the portion of the spread shocks (SPRDU) driven by volatility (or volatility shocks), and examine the orthogonal component of SPRDU for predicting future stock returns. To investigate this issue, we first run firm-level contemporaneous cross-sectional regressions of SPRDU on IVOL, and then use the residuals of these monthly cross-sectional regressions (that are orthogonal to idiosyncratic volatility) to form a univariate long-short equity portfolio. The first column in Table A5, Panel A, of the online Appendix shows that moving from Decile 1 to 10, the average return on SPRDU portfolios increases from 0.44% to 1.46% per month, with an average return difference of 1.02% per month with a t-statistic of 5.91 between low- and high-SPRDU portfolios. The corresponding alpha is 0.94%

[23] To test whether these findings are sensitive to alternative measures of liquidity shocks, we replicated our analysis in Table 5 using the shock to spread (SPRDU) and the conditional measure of liquidity shock (LIQCU). Specifically, we form 5 × 5 bivariate portfolios of VOLDU and SPRDU as well as IVOLU and SPRDU. We also form 5 × 5 bivariate portfolios of VOLDU and LIQCU as well as IVOLU and LIQCU. As presented in Table A4 of the online Appendix, within VOLDU and IVOLU quintiles, average returns on SPRDU and LIQCU portfolios increase monotonically as we move from the lowest to highest liquidity shock quintile. The average return and alpha differences between low- and high-liquidity shock portfolios are all positive and highly significant after controlling for VOLDU and IVOLU.

per month with a t-statistic of 5.17. Alternatively, we generate the orthogonal component of SPRDU with respect to volatility shocks (instead of volatility levels). We first run contemporaneous cross-sectional regressions of SPRDU on IVOLU, and then use the residuals that are orthogonal to volatility shocks to form a univariate portfolio. The last two columns of Table A5 show that moving from Decile 1 to 10, the average return on SPRDU portfolios increases from 0.61% to 1.37% per month, with an average return difference of 0.76% per month with a t-statistic of 4.51. The corresponding alpha is also positive, 0.77% per month, and highly significant with a t-statistic of 4.57. Panel B of Table A5 presents multivariate Fama-MacBeth regressions with the orthogonal components of SPRDU. The average slopes on SPRDU (orthogonal to IVOL and IVOLU) remain positive and highly significant after controlling for all other return predictors.

In sum, our liquidity shock measures continue to predict future returns after controlling for volatility and volume shocks, suggesting that the return predictability is consistent with stock market underreaction to liquidity shocks, rather than underreaction to volume or volatility shocks. In the following subsection, we perform multivariate Fama-MacBeth regressions of liquidity shocks on future returns while simultaneously controlling for an extensive list of variables.

2.4 Stock-level cross-sectional regressions

While portfolio-level analysis has an advantage of being nonparametric, it does not allow us to account for all the control variables jointly. 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:

$$R_{i,t+1} = \alpha_{t+1} + \gamma_{t+1} LIQ_{i,t}^{shock} + \varphi_{t+1} X_{i,t} + \varepsilon_{i,t+1}, \tag{6}$$

where $R_{i,t+1}$ is the realized excess return on stock i in month $t+1$, and $LIQ_{i,t}^{shock}$ represents one of the three alternative measures of liquidity shock of stock i in month t: LIQU, SPRDU, and LIQCU. $X_{i,t}$ is a vector of control variables for stock i in month t.

We start with the baseline model, where the control variables are the market beta (BETA), log market capitalization (LNME), and log book-to-market ratio (LNBM). We then add the other usual suspects, including the momentum (MOM), short-term reversal (REV), co-skewness (COSKEW), idiosyncratic volatility (IVOL), maximum daily return in the previous month (MAX), analyst dispersion (DISP), and the Amihud illiquidity measure (ILLIQ). Next, we add a variety of liquidity-based variables including the coefficient of variance in the Amihud illiquidity (CVILLIQ), standard deviation of turnover (SDTURN), Pastor and Stambaugh (2003) liquidity beta (PS), Acharya and Pedersen (2005) liquidity betas (BETA1 to BETA4), exposures to the fixed and the variable components of the Sadka liquidity factor (SADKAF and SADKAS), unexpected earnings (SUE), and two alternative measures of abnormal dollar trading volume: (i) the dummy variables for abnormal trading volume variable constructed following Gervais, Kaniel, and Mingelgrin (2001) (GKM_H for a stock with abnormally high dollar trading volume, GKM_L for a stock with abnormally low dollar volume); and (ii) abnormal dollar trading volume for a stock in month t relative to its prior 12-month average (VOLDU).[24]

Table 6 presents the time-series averages of the slope coefficients from the stock-level Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead stock returns on liquidity shocks with all cross-sectional predictors controlled for simultaneously, where abnormal trading volume in previous month is measured by either the dummy variables (GKM_H and GKM_L) or the continuous VOLDU variable. The t-statistics computed with Newey-West standard errors are shown in parentheses.[25]

Table 6 shows that, depending on the two alternative abnormal trading volume proxies used, the average slope coefficients of LIQU are 0.18 and 0.20 and highly significant. 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, the difference in LIQU values between average stocks in the high- and low-LIQU deciles is 2.22. Hence, the average slopes of 0.20 and 0.18 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 0.44% and 0.40%, controlling for everything else.[26]

Similarly, the average slope coefficients of SPRDU are 0.554 and 0.632, respectively, and highly significant, implying that a portfolio short-selling stocks with the largest increase in spread (stocks in Decile 1) and buying stocks with the largest decrease in spread (stocks in Decile 10) will yield a return in the following month by between 1.04% and 0.90%, controlling for everything else.[27] Finally, the average slope coefficients of LIQCU are 0.18 and 0.15, respectively, and highly significant, implying that a portfolio short-selling

[24] In some specifications we also control for shocks to idiosyncratic volatility and find this variable to be insignificant. To streamline the presentation, we defer those specifications to Table A6 of the online Appendix.

[25] Table A7 in the online Appendix reports the time-series averages of the slope coefficients from the stock-level Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead stock returns on liquidity shocks and various combinations of the control variables. The average slope coefficients of the liquidity shock proxies remain positive and significant at the 1% level based on the Newey-West t-statistics.

[26] Note that Table 6 does not include SPRD as a control variable when liquidity shocks are measured by LIQU or LIQCU, as employing SPRD greatly reduces the length of the sample. For robustness check, we include SPRD as a control variable for these two liquidity shock measures and find the results to be similar. The results are shown in Panels A and C of Table A7.

[27] At an earlier stage of the study, we construct a liquidity shock measure based on the equal-weighted quoted spread (QSPRD). This alternative measure of liquidity shock is calculated as the negative of QSPRD less the past 12-month average of QSPRD. The results are qualitatively similar to those based on the volume-weighted relative effective spread, and are summarized in Table A8 of the online Appendix.

Table 6
Stock-level cross-sectional regressions

Variable	LIQU		SPRDU		LIQCU	
	(1)	(2)	(1)	(2)	(1)	(2)
LIQ-Shock	0.201	0.175	0.632	0.554	0.179	0.146
	(5.00)	(4.36)	(7.41)	(6.80)	(5.12)	(3.59)
BETA	0.156	0.171	0.264	0.278	0.175	0.188
	(1.41)	(1.56)	(2.19)	(2.32)	(1.57)	(1.69)
LNME	−0.066	−0.096	−0.065	−0.081	−0.044	−0.085
	(−2.03)	(−2.94)	(−1.58)	(−1.99)	(−1.35)	(−2.59)
LNBM	0.140	0.125	0.101	0.091	0.148	0.126
	(1.82)	(1.65)	(1.20)	(1.09)	(1.95)	(1.68)
MOM	0.005	0.003	0.004	0.002	0.005	0.003
	(3.33)	(2.04)	(2.04)	(1.18)	(3.20)	(2.05)
REV	−0.033	−0.048	−0.028	−0.041	−0.034	−0.048
	(−6.13)	(−8.84)	(−5.20)	(−7.77)	(−6.18)	(−8.64)
COSKEW	0.119	0.105	0.731	0.689	0.280	0.252
	(0.15)	(0.13)	(0.87)	(0.83)	(0.36)	(0.33)
IVOL	−0.307	−0.383	−0.247	−0.334	−0.279	−0.356
	(−6.47)	(−7.89)	(−4.24)	(−5.49)	(−5.62)	(−7.17)
MAX	−0.012	−0.002	−0.018	−0.011	−0.009	0.000
	(−1.25)	(−0.21)	(−1.58)	(−0.96)	(−0.90)	(−0.01)
DISP	−0.070	−0.064	−0.09	−0.08	−0.079	−0.074
	(−2.27)	(−2.07)	(−2.32)	(−2.17)	(−2.51)	(−2.37)
SPRD			0.059	0.102		
			(0.88)	(1.50)		
ILLIQ	0.051	0.032	0.176	0.154	0.068	0.052
	(1.95)	(1.32)	(4.55)	(4.09)	(2.63)	(2.08)
CVILLIQ	0.098	0.034	0.102	0.032	0.112	0.045
	(1.66)	(0.58)	(1.51)	(0.47)	(1.81)	(0.74)
SDTURN	−0.271	−0.226	−0.233	−0.176	−0.263	−0.215
	(−2.94)	(−2.51)	(−2.43)	(−1.86)	(−2.83)	(−2.36)
PS	0.001	0.001	0.001	0.001	0.002	0.002
	(1.28)	(1.18)	(0.96)	(0.89)	(1.44)	(1.34)
BETA1	0.180	0.181	0.210	0.215	0.136	0.138
	(0.95)	(0.97)	(0.97)	(1.01)	(0.68)	(0.70)
BETA2	−4.367	−3.606	2.963	2.869	−5.019	−3.544
	(−1.14)	(−0.96)	(0.82)	(0.81)	(−1.15)	(−0.83)
BETA3	1.638	1.541	3.977	3.874	2.020	1.871
	(1.27)	(1.21)	(3.28)	(3.22)	(1.43)	(1.34)
BETA4	−0.325	−0.334	−0.098	−0.091	−0.570	−0.571
	(−0.98)	(−1.02)	(−0.28)	(−0.27)	(−1.38)	(−1.40)
SADKAF	−0.004	−0.004	0.000	0.000	−0.004	−0.003
	(−1.12)	(−1.16)	(−0.03)	(0.01)	(−1.11)	(−1.10)
SADKAV	−0.016	−0.016	−0.011	−0.010	−0.016	−0.015
	(−1.82)	(−1.80)	(−1.07)	(−0.99)	(−1.76)	(−1.70)
SUE	0.303	0.283	0.276	0.254	0.303	0.283
	(13.77)	(12.99)	(11.13)	(10.42)	(13.82)	(13.07)
GKM_H	0.547		0.523		0.537	
	(5.64)		(4.76)		(5.22)	
GKM_L	−0.071		−0.136		−0.079	
	(−1.10)		(−1.85)		(−1.17)	
VOLDU		0.210		0.186		0.200
		(9.77)		(7.84)		(9.35)

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 and Newey-West t-statistics in parentheses. LIQU denotes the liquidity shock, defined as the negative Amihud (2002) illiquidity measure (ILLIQ), demeaned using the past 12-month ILLIQ as the mean. SPRDU is the shock to the monthly volume-weighted effective relative spread (SPRD), calculated in the same fashion as LIQU. LIQCU denotes the conditional measure of liquidity shock, defined as the negative of the difference between the realized ILLIQ and the conditional mean of ILLIQ in the month estimated under the assumption that the conditional mean of ILLIQ follows an ARMA(1,1) process. 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. SUE is the standardized unexpected earnings. CVILLIQ is the coefficient of variation in the Amihud illiquidity measure. SDTURN denotes the standard deviation of the monthly turnover over the past 12 months. PS is Pastor and Stambaugh (2003) liquidity beta. BETA1–BETA4 are the Acharya and Pedersen (2005) four liquidity betas. SADKAF and SADKAV are the loadings on the fixed and the variable components of the Sadka (2006) liquidity factor. GKM_H and GKM_L denote the high- and low-volume dummy variables. VOLDU measures the abnormal dollar trading volume.

stocks with the largest decrease in liquidity (stocks in Decile 1) and buying stocks with largest increase in liquidity (stocks in Decile 10) will generate a return in the following month by between 0.42% and 0.35%, controlling for everything else.[28]

The average slope coefficients on the control variables are in line with the earlier studies. Specifically, the negative coefficient on stock size is consistent with Fama and French (1992, 1993). MOM is positive, while REV is negative, consistent with price momentum (Jegadeesh and Titman 1993) and short-term reversal (Jegadeesh 1990). Idiosyncratic volatility is negative and significant as in Ang and colleagues (2006). Analysts earnings forecast dispersion is negative and significant as in Diether, Malloy, and Scherbina (2002). The level of Amihud illiquidity is positive and significant, consistent with illiquidity premium shown in Amihud and Mendelson (1986) and subsequent studies. While the variation in illiquidity is positive but insignificant, standard deviation in turnover is negative and significant as in Chordia, Subrahmanyam, and Anshuman (2001) and Pereira and Zhang (2010). The exposure to systematic liquidity risk as proposed by Pastor and Stambaugh (2003) is positive, albeit insignificant. The exposure to the four Acharya and Pedersen (2005) betas are largely insignificant, with the exception of BETA3 when liquidity shocks are measured by SPRDU. Similarly, the Sadka (2006) fixed and variable liquidity betas are insignificant. Earnings surprises are positive and highly significant, consistent with earnings momentum as documented by Bernard and Thomas (1989) and subsequent papers. The high-volume dummy variable, GKM_H, and abnormal trading volume variable, VOLDU, are both positive and significant, consistent with the high-volume return premium proposed by Gervais, Kaniel, and Mingelgrin (2001).

Overall, the Fama-MacBeth regression results confirm that, even after jointly controlling for a large set of variables, our liquidity shock variables have economically and statistically significant predictive power for future stock returns. Furthermore, although liquidity shocks may appear to be related to changes in trading volume, the effect of liquidity shocks on future returns remain robust after controlling for the Gervais, Kaniel, and Mingelgrin (2001) high-volume return premium effect.

3. Investigating the Underlying Mechanism of Underreaction

Our finding of the positive link between stock-level liquidity shocks and future stock returns is inconsistent with the setting in which public information is incorporated into prices immediately. In such settings, given that liquidity shocks have persistent effects and that the level of illiquidity is found to be positively priced, negative liquidity shocks should lead to a higher risk premium

[28] As reported in the online Appendix, Panels A and B of Table A1 show that the differences in SPRDU and LIQCU values between average stocks in high- and low-liquidity shock deciles are 1.64 and 2.36, respectively.

and thus an instantaneous price decrease (lower contemporaneous return) and higher future returns. The opposite should be true for positive liquidity shocks.

As described earlier, Table 2 shows a positive contemporaneous relation between liquidity shocks and stock returns. This initial reaction of liquidity shocks is consistent with the argument put forth in the prior literature: a negative liquidity shock should lead to an immediate decrease in the stock price due to a higher illiquidity premium and vice versa. However, Tables 3–6 show that the market reaction is incomplete in the contemperaneous month, and future stock returns continue to drift positively with the past liquidity shocks. Our evidence thus suggests that the market underreacts to the liquidity shocks. The full effect of liquidity shocks is reflected in prices only gradually over time, resulting in return continuations in the following months.

To gain insight on the horizon of the underreaction, we examine the effect of liquidity shocks on future returns over various holding periods. We form long-short equity portfolios based on past liquidity shocks and investigate the performance of high versus low liquidity shock (LIQU) portfolios over months $t+1$ to $t+12$. Figure 1 depicts the monthly return differences between the highest LIQU and lowest LIQU deciles for 1 to 12 months after portfolio formation. The dashed lines indicate the 95% confidence bands, calculated based on the Newey and West (1987) standard errors. The figure shows that the return differentials between the highest LIQU and lowest LIQU deciles continue to be positive for up to 7 months after the shock. This evidence suggests that there exists considerable underreaction to stock-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 studies. 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 underreaction, which results in return predictability for 10 months or longer (especially for stocks with low analyst coverage). Hirshleifer, Lim, and Teoh (2009) show that the underreaction to earnings news surrounded 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. Kahneman's (1973) theory of attention indicates that attention is a scarce cognitive resource. Subsequently, a large body of psychological research shows that there is a limit to the central cognitive-processing capacity of the human brain.[29] The implication of attention theory in financial markets is that limited availability of time and cognitive resources imposes constraints on how fast

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

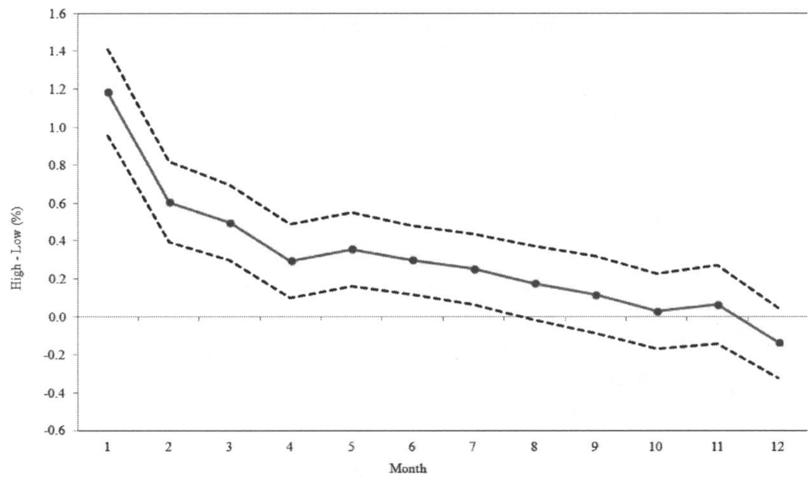

Figure 1
Monthly return differences between the highest and lowest LIQU deciles for 1 to 12 months after portfolio formation
This figure depicts the monthly return differences between the highest and lowest LIQU deciles for 1 to 12 months after portfolio formation. LIQU is the liquidity shock, defined as the negative Amihud (2002) illiquidity measure (ILLIQ), demeaned using the past 12-month ILLIQ as the mean. The dashed lines indicate the 95% confidence bands based on the Newey-West robust standard errors.

investors can process information. Theoretical models have shown that limited investor attention can lead to securities market underreaction to information and thus slow price adjustments (Hirshleifer and Teoh 2003; Peng 2005; Peng and Xiong 2006; Hirshleifer, Lim, and Teoh 2009). These predictions have been confirmed by recent empirical findings that securities prices underreact to value-relevant public information due to limited investor attention.[30]

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

Illiquidity may also result in delays in price adjustments: if information is revealed through trading, then for illiquid stocks that are harder to trade,

[30] See, for example, Huberman and Regev (2001), Hirshleifer et al. (2004), Hou and Moskowitz (2005), Hong, Torous, and Valkanov (2007), DellaVigna and Pollett (2007, 2009), Cohen and Frazzini (2008), Hirshleifer, Lim, and Teoh (2009), and Hirshleifer, Hsu, and Li (2013).

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 investors 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 react to public information, prices can be updated without 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 (2013), we adopt stock size and analyst coverage as proxies for investor attention. Smaller stocks and stocks with lower analyst coverage receive less attention from investors. As a result, we expect these stocks to exhibit more delayed reaction to information contained in liquidity shocks, and thus liquidity shocks can generate greater return predictability. Small stocks and stocks with lower analyst coverage have slower information diffusions, which is 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 sale constraints. The attention-based underreaction mechanism predicts that there should be a stronger positive relation between liquidity shocks and future returns for small stocks, and stocks with low analyst coverage and low institutional ownerships.

To test this prediction, we first sort stocks into quintile portfolios based on an attention proxy, and then within each proxy quintile, we sort the stocks into liquidity shock quintile portfolios. We follow the prior literature (for example, Hong, Lim, and Stein 2000) and use the NYSE breakpoints. Table 7 presents

5×5 bivariate portfolio returns and return differentials, with Newey-West t-statistics reported in parentheses. Panels A–C use stock size, analyst coverage, and institutional ownership as alternative proxies for investor attention.

Panel A shows that a portfolio that is long in stocks with positive liquidity shocks (increases in liquidity) and short in stocks with negative liquidity shocks (decreases in liquidity) leads to a monthly return of 145 basis points for stocks in the smallest size quintile and a return of only 43 basis points for stocks in the largest size quintile. The difference is 102 basis points per month, and statistically significant. Results are similar with the risk-adjusted returns; the Fama-French three-factor alpha on the long-short portfolio based on LIQU is 1.50% per month in the smallest size quintile, whereas the corresponding alpha is only 0.52% per month in the biggest size quintile, the difference is significant at 98 basis points per month.

Panels B and C show similar results. The return differential for the long-short portfolio based on LIQU is high for the quintile with the lowest analyst coverage and institutional ownership, 128 and 147 basis points per month, respectively, and lower for the quintile with the highest analyst coverage and institutional ownership, 49 and 71 basis points per month. The difference of long-short portfolio return differential across analyst coverage and institutional ownership quintile is highly significant for both the raw returns and for the abnormal returns. It is also worth noting that Kaniel, Ozoguz, and Starks (2012) find that the high-volume return premium effect originally documented by Gervais, Kaniel, and Mingelgrin (2001) is actually increasing in analyst coverage, contrary to our finding that the return predictability of liquidity shocks is decreasing in analyst coverage. This disparity further suggests that the two effects are distinct.

Overall, these results support the attention-based underreaction hypothesis that the market's 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.

To test whether illiquidity-driven slow price adjustment can also contribute to the market's 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 illiquidity measure (ILLIQ), and then within each ILLIQ quintile, stocks are sorted into quintiles on liquidity shocks (LIQU). Panel D of Table 7 reports the average returns for each of the 5×5 portfolios of ILLIQ and LIQU, the return difference (high−low) between the highest and the lowest LIQU quintiles within each ILLIQ quintile, and the three-factor alpha. The return differences and three-factor alphas remain significantly positive across all ILLIQ quintiles. Moving from the lowest to the highest ILLIQ quintile, the return difference between Quintile 5 and Quintile 1 LIQU portfolios increases from 52 to 136 basis points per month, and the corresponding three-factor alpha increases from 49 to 138 basis points per month. These return and alpha spreads are also highly significant without any

Table 7
Bivariate sorts controlling for attention and liquidity

Panel A: Control for LNME

LIQU	LNME (Low)	LNME 2	LNME 3	LNME 4	LNME (High)	High–Low
1 (Low)	0.41	0.76	0.74	0.82	0.64	0.22
2	0.77	1.00	1.02	0.98	0.89	0.11
3	1.33	1.23	1.26	1.13	0.98	−0.35
4	1.72	1.45	1.33	1.19	0.89	−0.84
5 (High)	1.87	1.58	1.39	1.23	1.07	−0.80
High–Low	1.45	0.82	0.66	0.40	0.43	−1.02
	(10.96)	(5.27)	(4.16)	(2.66)	(2.98)	(−7.54)
Alpha	1.50	0.95	0.75	0.54	0.52	−0.98
	(11.51)	(5.80)	(4.33)	(3.32)	(3.51)	(−7.16)

Panel B: Control for CVRG

LIQU	CVRG (Low)	CVRG 2	CVRG 3	CVRG 4	CVRG (High)	High–Low
1 (Low)	0.61	0.78	0.95	1.02	0.78	0.17
2	0.89	1.09	1.11	1.05	1.02	0.13
3	1.26	1.19	1.23	1.02	1.05	−0.21
4	1.62	1.32	1.18	1.18	1.03	−0.59
5 (High)	1.89	1.70	1.52	1.35	1.27	−0.62
High–Low	1.28	0.92	0.57	0.33	0.49	−0.79
	(8.14)	(5.01)	(2.70)	(1.71)	(2.11)	(−3.90)
Alpha	1.32	1.00	0.62	0.42	0.51	−0.81
	(8.40)	(5.89)	(3.07)	(2.11)	(2.24)	(−3.89)

Panel C: Control for INST

LIQU	INST (Low)	INST 2	INST 3	INST 4	INST (High)	High–Low
1 (Low)	0.23	0.50	0.74	0.75	0.72	0.49
2	0.54	0.98	1.22	1.15	1.09	0.55
3	1.04	1.03	1.26	1.20	1.11	0.07
4	1.55	1.36	1.22	1.20	1.13	−0.42
5 (High)	1.70	1.84	1.57	1.55	1.33	−0.37
High–Low	1.47	1.34	0.82	0.79	0.61	−0.86
	(9.18)	(7.34)	(4.32)	(4.15)	(3.16)	(−4.71)
Alpha	1.56	1.46	1.01	0.98	0.82	−0.74
	(10.80)	(8.82)	(5.58)	(5.53)	(4.59)	(−4.33)

Panel D: Control for ILLIQ

LIQU	ILLIQ (Low)	ILLIQ 2	ILLIQ 3	ILLIQ 4	ILLIQ (High)	High–Low
1 (Low)	0.73	0.82	0.79	0.67	0.45	−0.29
2	0.94	0.98	1.03	1.03	0.78	−0.15
3	0.99	1.18	1.24	1.19	1.18	0.19
4	0.98	1.17	1.31	1.39	1.65	0.68
5 (High)	1.26	1.30	1.45	1.75	1.81	0.55
High–Low	0.52	0.47	0.66	1.08	1.36	0.84
	(3.44)	(2.60)	(3.24)	(5.34)	(10.56)	(6.00)
Alpha	0.49	0.58	0.69	1.12	1.38	0.89
	(3.03)	(3.23)	(3.24)	(5.25)	(10.99)	(6.07)

Stocks are sorted into quintile portfolios based on an investor attention variable or the Amihud illiquidity measure (ILLIQ) and then into quintile portfolios of liquidity shock (LIQU) within each control quintile using NYSE breakpoints. The investor attention variables are the natural logarithm of market capitalization (LNME), the number of analysts covering the stocks (CVRG), and the quarterly aggregate institutional holdings (INST). This table reports the average returns for each of the 5×5 portfolios, the return differences between high- and low-LIQU quintile portfolios within each control variable quintile portfolio and the Fama-French (1993) alphas. The last column presents the 5–1 average return differences for each control variable within each LIQU quintile portfolio. Newey-West t-statistics are given in parentheses.

exception. These results are consistent with the illiquidity-based underreaction hypothesis that the market's underreaction to liquidity shocks is stronger for less-liquid stocks.

The evidence thus far seems to be consistent with both the attention- and the illiquidity-based underreaction hypotheses. It could be argued 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 stock size (LNME), analyst coverage (CVRG), and institutional ownership (INST) are −0.41, −0.26, and −0.24, respectively. Although these correlations are not high in absolute terms, what the attention measures capture can potentially be the effect of liquidity, and vice versa. To disentangle the effect of investor attention from illiquidity and gauge the relative importance of the two mechanisms in contributing to the market's underreaction to liquidity shocks, we include both underreaction proxies and illiquidity as interaction variables with LIQU in Fama-MacBeth regressions.

In Table 8, the cross-section of one-month-ahead excess returns are regressed against the liquidity shock proxies (LIQU, SPRDU, LIQCU), the illiquidity level (ILLIQ), the interaction between the illiquidity level and liquidity shock, and the interaction between one attention proxy (LNME, CVRG, INST) and liquidity shock, along with the same set of controls that are used in Table 6.

Panel A reports the Fama-MacBeth regression coefficients when liquidity shocks are measured by LIQU.[31] The results show that the average slope coefficient on $(LIQU \times ATTENTION)$ is negative and highly significant across all three attention proxies (LNME, CVRG, and INST), suggesting that the return predictability of liquidity shocks is stronger for low-attention stocks, even after controlling for any potential effect of illiquidity levels. The average slope on $(LIQU \times ILLIQ)$ is positive and marginally significant when investor attention is proxied by LNME, but it is statistically insignificant when investor attention is proxied by CVRG and INST. This suggests that illiquidity-driven slow price adjustment may also be a contributing factor to the market's underreaction to liquidity shocks, although its impact is weaker compared with the attention mechanism.

In Panel B of Table 8, we use SPRDU as the proxy for liquidity shock and run the same set of cross-sectional regressions with interaction variables. Similar to our earlier findings reported in Panel A, the average slope coefficient on $(SPRDU \times ATTENTION)$ is negative and significant for both Models 1 and 2, across all three attention proxies. In contrast, the average slope coefficient on $(SPRDU \times ILLIQ)$ is positive and significant only when

31 We suppress the coefficient estimates of the cross-sectional controls. They are presented in Table A10 of the online Appendix.

Table 8
Monthly Fama-MacBeth regressions with interaction terms

Panel A: Liquidity shock measured by LIQU

	LNME		CVRG		INST	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
LIQU	0.908	0.979	0.603	0.572	0.403	0.320
	(4.68)	(4.80)	(6.82)	(6.54)	(6.79)	(5.76)
LIQU×ILLIQ	0.100	0.086	0.100	0.055	0.027	0.003
	(1.93)	(1.66)	(1.07)	(0.60)	(0.54)	(0.06)
LIQU×ATTENTION	−0.111	−0.148	−0.180	−0.234	−0.234	−0.304
	(−3.34)	(−4.12)	(−3.11)	(−3.94)	(−2.01)	(−2.56)

Panel B: Liquidity shock measured by SPRDU

SPRDU	1.721	1.650	0.825	0.753	0.788	0.679
	(7.37)	(7.06)	(5.71)	(5.26)	(6.56)	(5.85)
SPRDU×ILLIQ	0.322	0.272	0.019	0.043	0.116	0.057
	(3.36)	(2.87)	(0.09)	(0.20)	(1.14)	(0.55)
SPRDU×ATTENTION	−0.228	−0.237	−0.313	−0.335	−0.815	−0.836
	(−5.71)	(−5.82)	(−3.76)	(−3.99)	(−4.17)	(−4.26)

Panel C: Liquidity shock measured by LIQCU

LIQCU	0.329	0.353	0.230	0.216	0.241	0.197
	(3.39)	(3.62)	(3.78)	(3.51)	(3.87)	(3.38)
LIQCU×ILLIQ	0.088	0.081	0.111	0.082	0.092	0.073
	(2.45)	(2.28)	(1.27)	(0.93)	(2.42)	(2.04)
LIQCU×ATTENTION	−0.032	−0.046	−0.050	−0.073	−0.237	−0.261
	(−1.87)	(−2.67)	(−1.53)	(−2.15)	(−1.90)	(−2.04)

One-month-ahead excess returns are regressed on the Amihud illiquidity measure (ILLIQ), one investor attention variable, the liquidity shock (LIQ-Shock), and the interactions between ILLIQ and LIQ-Shock and between the attention variable and LIQ-Shock using the Fama-MacBeth (1973) methodology. LIQ-Shock is measured by LIQU in Panel A, SPRDU in Panel B, and LIQCU in Panel C. The investor attention variables are the natural logarithm of market capitalization (LNME), the number of analysts covering the stocks (CVRG), and the quarterly aggregate institutional holdings (INST). We simultaneously control for a large set of cross-sectional predictors: the investor attention variable (controlled for one at a time), the market beta (BETA), LNME, 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 standardized unexpected earnings (SUE), the high- and low-volume dummy variables (GKM_H and GKM_L), the dollar trading volume shock (VOLDU), the standard deviation of the monthly turnover over the past 12 months (SDTURN), the coefficient of variation in the Amihud illiquidity measure (CVILLIQ), Pastor and Stambaugh (2003) liquidity beta (PS), the Acharya and Pedersen (2005) four liquidity betas (BETA1–BETA4), and the loadings on the fixed and the variable components of the Sadka (2006) liquidity factor (SADKAF and SADKAV). Specifications (1) and (2) control for the GKM dummy variables (GKM_H and GKM_L) and the abnormal dollar trading volume (VOLDU), respectively. For brevity, we suppress the average slope coefficients of the control variables, which are available in Table A10 of the online Appendix. Newey-West t-statistics are given in parentheses.

investor attention is proxied by LNME, and insignificant for the other two attention proxies.

In Panel C of Table 8, we use LIQCU as the proxy for liquidity shock. Similar to findings in Panels A and B, the average slope coefficient on $(LIQCU \times ATTENTION)$ is negative and significant across all three attention proxies, except in Model (1) when investor attention is proxied by CVRG. The coefficient on $LIQCU \times ILLIQ$ is positive and significant when size and institutional ownership are used as attention proxies, but not when analyst coverage is used. The different level of significance of the attention interaction variable and the illiquidity interaction variable suggests that these two interaction variables are not capturing the same effect.

To summarize, the positive relation between liquidity shocks and one-month-ahead stock returns remains significant for all specifications, and the relation is stronger for low-attention stocks and for illiquid stocks. The results imply that the positive relation between liquidity shocks and future returns is due to the market's underreaction to liquidity shocks, which can be attributed to investor inattention and illiquidity.

Following Hong, Lim, and Stein (2000) and Hirshleifer, Lim, and Teoh (2009), we further investigate the attention and liquidity-based mechanisms by studying long-term cumulative returns. Table 9 reports the Fama-MacBeth average slope coefficients on LIQU with and without the interaction terms, and controlling for a large set of control variables listed earlier.[32] Similar to Table 8, models (1) and (2) use GKM_H, GKM_L, and VOLDU to capture abnormal dollar trading volume, respectively.

Panel A of Table 9 presents the benchmark model without interaction variables. It shows that, consistent with Figure 1, the positive link between liquidity shocks and future cumulative stock returns remains significant for at least six months into the future.

Panels B through D include attention and liquidity interaction variables. In Panel B of Table 9, LNME proxies for investor attention. The average slope coefficient on $(LIQU \times LNME)$ is negative and highly significant for six months into the future, indicating that the attention-based mechanism is important for explaining return continuations over the next six months. In contrast, the slope coefficient on $(LIQU \times ILLIQ)$ becomes insignificant starting month 2, indicating that the illiquidity-driven underreaction is short-lived.

Panels C and D of Table 9 present qualitatively similar evidence when analysts' coverage and institutional ownership are used as proxies for investor attention. The average slope coefficient on $(LIQU \times CVRG)$ is negative and highly significant up to five months into the future, and the average slope coefficient on $(LIQU \times INST)$ is negative and highly significant for two months into the future.

Overall, the results in Tables 8 and 9 suggest that, while inattention and illiquidity both contribute to short-term return predictability of liquidity shocks, the inattention-based mechanism is more important for the longer-run predictability. The regression results from long-term stock return prediction confirm the portfolio results in Figure 1 and demonstrate that the horizon of return predictability is consistent with other studies that document security market underreaction due to investor inattention (Bernard and Thomas 1989; Hong, Lim, and Stein 2000; Hirshleifer, Lim, and Teoh 2009).

32 We obtain similar results when liquidity shocks are measured either with SPRDU or LIQCU, the results are shown in Table A11 of the online Appendix.

Table 9
Predicting long-term stock returns

Panel A: Without interaction terms

Variable	2-Month (1)	2-Month (2)	3-Month (1)	3-Month (2)	4-Month (1)	4-Month (2)	5-Month (1)	5-Month (2)	6-Month (1)	6-Month (2)
LIQU	0.320	0.294	0.401	0.378	0.502	0.481	0.577	0.557	0.654	0.632
	(5.34)	(4.76)	(4.56)	(4.25)	(3.81)	(3.69)	(3.44)	(3.32)	(3.24)	(3.14)
Panel B: Interacting with ILLIQ and LNME										
LIQU	1.454	1.507	1.938	1.991	2.428	2.478	2.727	2.767	3.054	3.097
	(3.96)	(4.03)	(4.39)	(4.42)	(4.14)	(4.14)	(3.65)	(3.62)	(3.66)	(3.67)
LIQU×ILLIQ	0.133	0.125	0.194	0.189	0.214	0.218	0.221	0.223	0.222	0.232
	(1.35)	(1.31)	(1.71)	(1.70)	(1.30)	(1.38)	(1.05)	(1.07)	(0.93)	(1.01)
LIQU×LNME	−0.198	−0.228	−0.284	−0.315	−0.375	−0.402	−0.420	−0.444	−0.471	−0.496
	(−3.02)	(−3.36)	(−3.53)	(−3.79)	(−3.59)	(−3.73)	(−3.16)	(−3.21)	(−3.22)	(−3.32)
Panel C: Interacting with ILLIQ and CVRG										
LIQU	0.999	0.956	1.097	1.052	1.235	1.186	1.222	1.169	1.315	1.264
	(5.99)	(5.70)	(4.52)	(4.30)	(3.84)	(3.68)	(3.04)	(2.90)	(2.75)	(2.62)
LIQU×ILLIQ	0.199	0.147	0.089	0.024	0.057	0.020	0.115	0.192	0.232	0.323
	(1.23)	(0.90)	(0.34)	(0.09)	(0.17)	(0.06)	(0.27)	(0.43)	(0.41)	(0.54)
LIQU×CVRG	−0.393	−0.448	−0.468	−0.523	−0.567	−0.614	−0.543	−0.579	−0.566	−0.599
	(−3.49)	(−3.91)	(−2.94)	(−3.26)	(−2.72)	(−2.89)	(−2.04)	(−2.13)	(−1.82)	(−1.91)
Panel D: Interacting with ILLIQ and INST										
LIQU	0.613	0.541	0.690	0.617	0.770	0.709	0.820	0.764	0.862	0.810
	(6.04)	(5.22)	(4.70)	(4.18)	(3.70)	(3.38)	(3.17)	(2.94)	(2.78)	(2.57)
LIQU×ILLIQ	0.035	0.016	0.058	0.039	0.050	0.041	0.012	0.003	0.035	0.036
	(0.51)	(0.24)	(0.59)	(0.41)	(0.32)	(0.28)	(0.06)	(0.02)	(0.15)	(0.16)
LIQU×INST	−0.552	−0.607	−0.673	−0.723	−0.816	−0.851	−0.835	−0.865	−0.809	−0.838
	(−2.07)	(−2.20)	(−1.86)	(−1.92)	(−1.56)	(−1.81)	(−1.54)	(−1.58)	(−1.26)	(−1.30)

Excess cumulative returns in two to six months into the future are regressed on a set of predictive variables measured in month t using the Fama and MacBeth (1973) methodology. This table reports the average slope coefficients of LIQU (in Panel A), and LIQU and the interactions between ILLIQ and LIQU and between LIQU and an attention variable–LNME in Panel B, CVRG in Panel C and INST in Panel D. Specifications (1) and (2) control for the GKM dummy variables (GKM_H and GKM_L) and the abnormal dollar trading volume (VOLDU), respectively. We simultaneously control for the market beta (BETA), LNME, 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 standardized unexpected earnings (SUE), the high- and low-volume dummy variables (GKM_H and GKM_L), the abnormal dollar volume (VOLDU), the standard deviation of the monthly turnover over the past 12 months (SDTURN), the coefficient of variation in the Amihud illiquidity measure (CVILLIQ), Pastor and Stambaugh (2003) liquidity beta (PS), the Acharya and Pedersen (2005) four liquidity betas (BETA1–BETA4), and the loadings on the fixed and the variable components of the Sadka (2006) liquidity factor (SADKAF and SADKAV). We suppress the average coefficients of the control variables, which are available upon request.The t-statistics (in parentheses) are based on Hodrick (1992) robust standard errors.

4. Robustness

In this section, we show that our results are robust to market microstructure effects, for different stock exchanges, and during different subsample periods.

4.1 Market microstructure effects

Previously, we addressed the concern that our results may be driven by market microstructure effects such as bid-ask bounce by controlling for past month returns, as well as various microstructure measures (illiquidity, spreads, etc.). In this subsection, we provide an additional robustness check by measuring liquidity shocks in month $t-2$ and predicting the cross-section of stock returns in month t. In other words, we skip a month between the liquidity shock estimation and the return prediction. Table 10 presents the average returns on the equal-weighted and value-weighted portfolios after skipping the month. As shown in the last two rows of Table 10, the equal-weighted (value-weighted) raw return differences and the corresponding alphas are, respectively, 0.60% and 0.70% (0.58% and 0.65%) per month between the high- and low-LIQU portfolios and significant at the 1% level based on the Newey-West t-statistics. These positive and significant return and alpha spreads, together with the long-run predictive regression results shown in Table 9, confirm that the predictive power of liquidity shocks goes beyond the next month and is unlikely to be driven by short-term microstructure effects.

In Section 2.3, we investigate the one-month-ahead predictive power of liquidity shocks after controlling for volume and volatility shocks using double-sorted portfolios. We now test whether liquidity shocks can continue to predict two-month-ahead returns after controlling for volume and volatility shocks, again with double-sorted portfolios.

Panel B of Table 10 shows that after controlling for VOLDU, the two-month-ahead return ($t+2$ return) on LIQU portfolios averaged across the VOLDU quintiles increases from 0.99% to 1.49% per month, with an average return difference of 50 basis points per month between low- and high-LIQU portfolios, and is highly significant with a t-statistic of 5.01. The corresponding alpha is also 0.50% per month with a t-statistic of 5.34. After controlling for IVOLU, $t+2$ return on LIQU portfolios averaged across the IVOLU quintiles increases monotonically from 0.91% to 1.53% per month, with an average return difference of 62 basis points per month (t-statistic = 5.25). The corresponding alpha is 0.69% per month, and highly significant with a t-statistic of 6.11. As shown in Table A12 of the online Appendix, similar results are obtained when we replicate Panel B of Table 10 by replacing LIQU with alternative measures of liquidity shocks (SPRDU and LIQCU). These results suggest that the longer-term return predictability of liquidity shocks is robust with respect to volume shocks or volatility shocks.

To address the issue of bid-ask bounce more directly, we measure stock returns using the quoted bid-ask midpoints and then replicate our main findings for the period of 1993–2010. The monthly stock returns are calculated based on the quote midpoint, which is the average of the monthly closing national best bid and offer (NBBO) and adjusted for dividends and stock splits.

In Table A13 of the online Appendix, we report the equal- and value-weighted average one-month-ahead quote midpoint returns for decile portfolios formed on liquidity shocks. Panel A shows that the average return differences between high- and low-liquidity shock deciles and the corresponding Fama-French alphas are positive and highly significant for all measures of liquidity shocks (LIQU, SPRDU, and LIQCU). More important, both the economic

Table 10
Two-month-ahead return predictability

Panel A: Univariate portfolio sorts

	Equal-weighted		Value-weighted	
Decile	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.90	−0.40	0.88	−0.34
	(3.19)	(−5.05)	(3.40)	(−3.81)
2	0.99	−0.20	0.95	−0.13
	(3.75)	(−2.21)	(4.01)	(−1.51)
3	1.01	−0.11	0.96	−0.05
	(4.16)	(−1.34)	(4.33)	(−0.61)
4	1.05	−0.06	1.00	−0.04
	(4.38)	(−0.80)	(4.53)	(−0.57)
5	1.05	−0.05	0.94	−0.07
	(4.45)	(−0.77)	(4.17)	(−1.08)
6	1.00	−0.10	1.06	0.05
	(4.36)	(−1.57)	(5.00)	(0.82)
7	1.08	−0.01	1.10	0.13
	(4.57)	(−0.13)	(5.08)	(1.96)
8	1.06	−0.04	1.09	0.11
	(4.35)	(−0.73)	(4.67)	(1.47)
9	1.24	0.09	1.23	0.17
	(4.83)	(1.69)	(5.05)	(2.64)
10 (High)	1.51	0.31	1.46	0.31
	(5.30)	(4.38)	(5.39)	(4.33)
High–Low	0.60	0.70	0.58	0.65
	(5.56)	(6.59)	(4.20)	(4.67)

Panel B: Bivariate portfolio sorts

Quintile	Controlling for VOLDU	Controlling for IVOLU
1 (Low)	0.99	0.91
2	0.96	1.01
3	1.04	1.01
4	1.22	1.19
5 (High)	1.49	1.53
High–Low	0.50	0.62
	(5.01)	(5.25)
Alpha	0.50	0.69
	(5.34)	(6.11)

Panel A of this table reports the equal- and value-weighted two-month-ahead returns (month $t+2$) and the alphas with respect to the Fama-French (1993) factors for each decile portfolio formed on the liquidity shock measured by the negative Amihud illiquidity measure, demeaned using the past 12 months as the mean. The last row shows the monthly return differences between high- and low-LIQU decile portfolios and the alphas. Panel B reports average returns and return differences in month $t+2$ between high- and low-LIQU quintile portfolios and the alphas after controlling for the abnormal dollar trading volume (VOLDU) and the idiosyncratic volatility shock (IVOLU). Newey-West t-statistics are given in parentheses.

and statistical significance of the return and alpha spreads in Table A13 are very similar to those reported in Table 3. In addition to the portfolio results in Panel A, we present stock-level cross-sectional regressions from midquote returns in Panel B of Table A13. Panel B reports the average slope coefficients of liquidity shocks from the Fama-MacBeth regressions of one-month-ahead quote midpoint returns on liquidity shocks and all other control variables. A notable point in Panel B is that both the magnitude and statistical significance of the average slopes from quote midpoint returns are similar to those reported in Table 6. Overall, these results indicate that the economically and statistically significant link between liquidity shocks and future returns is not driven or magnified by microstructure effects.

We further account for the possibility that market microstructure effects can bias the Fama-MacBeth regression coefficients using the technique of Asparouhova, Bessembinder, and Kalcheva (2010). Specifically, we run monthly weighted least squares (WLS) regressions, where each observed return is weighted by the gross return on the same stock in the prior month. For our key variable, liquidity shocks, the coefficient estimates and t-statistics are slightly lower than our original results after correcting for microstructure biases, but they all remain positive and significant at the 5% level or better. The results presented in Table A14 of the online Appendix show that the predictive power of liquidity shocks is robust to potential microstructure-related biases.

4.2 Screen on stock exchanges

In this section, we provide evidence that our main findings are not driven by the inclusion of AMEX and NASDAQ stocks, and the results hold for big and liquid stocks in the S&P 500 sample.

We apply three types of screens by using stocks listed only on (i) NYSE/AMEX, (ii) NYSE, and (iii) S&P 500 index. Table 11 reports the one-month-ahead returns of the univariate portfolios sorted on LIQU for the three stock samples. The results show that the predictive ability of liquidity shocks remains strong. The NYSE/AMEX sample and the NYSE sample results are very similar to the full CRSP sample result documented in Table 3, with the long-short portfolio raw return differential ranging from 104 to 115 basis points per month for raw returns and 94 to 117 basis points per month for three-factor adjusted returns, all highly significant. Even for the S&P 500 sample, the return and alpha spreads from equal- and value-weighted portfolios remain economically large and statistically significant, ranging from 61 to 68 basis points per month, suggesting that underreaction to liquidity shocks is not restricted to small and illiquid stocks.

4.3 Recessionary versus expansionary periods

In Table 12, we examine whether our findings are sensitive to the state of the economy by examining the one-month-ahead returns on the long-short portfolio sorted on LIQU for different subsample periods. The first two columns of Panel A exclude the most recent financial crisis period (July 2007 to June 2009). For this sample, the long-short portfolio generates a return of 121 basis points per month, comparable to the full sample results presented in Table 3. The next four columns present results for NBER expansionary and recessionary periods, respectively. The raw returns from the long-short portfolio are stable across the business cycles, with a magnitude of 116 basis points for the expansionary periods and 130 basis points for the recessionary periods and statistically significant. The results suggest that the predictive power of liquidity shocks is robust to different states of the economy.

Table 11
Predicting one-month-ahead returns based on the NYSE/AMEX, NYSE and S&P 500 samples

	NYSE/AMEX				NYSE				S&P 500			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.58	−0.73	0.46	−0.75	0.89	−0.60	0.75	−0.63	0.83	−0.42	0.73	−0.41
	(2.06)	(−7.60)	(1.77)	(−6.86)	(3.76)	(−5.22)	(3.34)	(−4.83)	(3.12)	(−3.57)	(2.83)	(−3.30)
2	0.75	−0.49	0.67	−0.47	1.02	−0.41	0.95	−0.34	0.98	−0.14	0.90	−0.12
	(2.85)	(−5.08)	(2.75)	(−4.50)	(4.69)	(−3.50)	(4.77)	(−2.68)	(3.97)	(−1.29)	(3.85)	(−1.15)
3	0.95	−0.21	0.86	−0.20	1.15	−0.20	1.04	−0.18	0.95	−0.10	0.85	−0.12
	(3.82)	(−2.11)	(3.74)	(−2.03)	(5.82)	(−1.83)	(5.81)	(−1.70)	(4.10)	(−1.16)	(3.79)	(−1.41)
4	1.09	−0.05	1.06	0.02	1.28	−0.07	1.23	−0.01	1.04	0.03	0.95	0.02
	(4.63)	(−0.52)	(4.86)	(0.25)	(6.77)	(−0.77)	(6.95)	(−0.08)	(4.71)	(0.41)	(4.22)	(0.20)
5	1.08	−0.04	0.99	−0.04	1.31	−0.03	1.20	−0.03	1.07	0.08	1.00	0.07
	(4.52)	(−0.51)	(4.43)	(−0.52)	(6.91)	(−0.39)	(6.79)	(−0.33)	(5.10)	(1.39)	(4.87)	(1.05)
6	1.10	−0.02	1.04	0.01	1.34	−0.02	1.25	0.00	1.06	0.07	1.08	0.17
	(4.70)	(−0.30)	(4.91)	(0.19)	(7.06)	(−0.34)	(7.25)	(−0.04)	(5.06)	(0.96)	(5.51)	(2.60)
7	1.25	0.13	1.23	0.21	1.50	0.09	1.47	0.19	1.07	0.05	0.99	0.07
	(5.51)	(1.89)	(5.73)	(3.31)	(7.69)	(1.33)	(8.07)	(2.58)	(5.04)	(0.68)	(4.92)	(0.92)
8	1.29	0.11	1.18	0.10	1.54	0.06	1.43	0.04	1.22	0.20	1.14	0.19
	(5.39)	(1.45)	(5.30)	(1.35)	(7.54)	(0.88)	(7.70)	(0.59)	(5.56)	(2.63)	(5.39)	(2.43)
9	1.41	0.20	1.37	0.24	1.68	0.14	1.62	0.16	1.23	0.14	1.17	0.18
	(5.67)	(2.23)	(5.88)	(3.04)	(7.75)	(1.82)	(8.12)	(2.15)	(5.33)	(2.00)	(5.40)	(2.33)
10 (High)	1.72	0.44	1.61	0.40	1.96	0.34	1.79	0.21	1.46	0.26	1.34	0.23
	(6.22)	(5.33)	(6.22)	(4.87)	(8.14)	(3.66)	(7.82)	(2.23)	(5.87)	(3.11)	(5.53)	(2.76)
High–Low	1.14	1.17	1.15	1.14	1.07	0.94	1.04	0.84	0.63	0.68	0.61	0.65
	(10.43)	(10.51)	(8.48)	(8.24)	(9.60)	(6.90)	(7.25)	(5.23)	(4.32)	(4.71)	(3.76)	(3.98)

Columns "NYSE/AMEX," "NYSE," and "S&P 500" report the equal- and value-weighted monthly returns in month $t+1$ and the alphas with respect to the Fama-French (1993) factors for decile portfolios formed based on the liquidity shock (LIQU) in month t. The last row presents the differences in monthly returns between high- and low-LIQU decile portfolios and the alphas. Newey-West t-statistics are given in parentheses.

4.4 Subsample analysis

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.

Panel B of Table 12 shows that the average return differences and their alphas between the high- and low-LIQU portfolios are positive and highly significant for all decades. Specifically, the average raw return differences are, respectively, 1.41%, 1.09%, 0.96%, 1.75%, and 0.55% per month for the aforementioned decades, and are significant at the 5% level or better; the corresponding alpha differences are, respectively, 1.32%, 0.95%, 0.96%, 1.88%, and 0.67% per month, and are all highly significant as well. These results show that the strong positive link between liquidity shocks and future returns is robust across different sample periods.

5. Discussions of Alternative Mechanisms

We have shown that the positive relation between liquidity shocks and future returns is robust after controlling for a long list of alternative explanations, including the level and the variability of illiquidity, the exposure to systematic liquidity risk, microstructure effects, and high-volume return premium. In this section, we discuss whether our findings can be explained by other mechanisms.

Table 12
Subperiod analysis

Panel A: Returns on the liquidity shock portfolios in expansionary vs. recessionary periods

	Non-crisis periods		Expansionary periods		Recessionary periods	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.64	−0.74	0.77	−0.70	−0.87	−0.86
	(2.41)	(−7.71)	(3.09)	(−7.07)	(−0.86)	(−4.78)
2	0.81	−0.47	0.94	−0.46	−0.49	−0.26
	(3.25)	(−4.85)	(4.14)	(−4.60)	(−0.49)	(−1.21)
3	1.05	−0.18	1.13	−0.21	−0.09	0.15
	(4.55)	(−1.75)	(5.55)	(−2.11)	(−0.09)	(0.64)
4	1.14	−0.09	1.23	−0.10	0.01	0.26
	(5.13)	(−1.08)	(6.43)	(−1.18)	(0.01)	(1.39)
5	1.21	−0.02	1.29	−0.05	−0.03	0.25
	(5.47)	(−0.24)	(6.52)	(−0.63)	(−0.03)	(1.45)
6	1.18	−0.04	1.29	−0.06	−0.09	0.21
	(5.42)	(−0.58)	(6.59)	(−0.89)	(−0.10)	(1.34)
7	1.30	0.07	1.39	0.00	0.13	0.41
	(6.00)	(1.25)	(6.85)	(0.06)	(0.16)	(2.78)
8	1.35	0.06	1.46	0.02	0.01	0.25
	(5.73)	(1.07)	(6.66)	(0.32)	(0.02)	(1.26)
9	1.45	0.13	1.56	0.09	0.16	0.41
	(5.79)	(2.17)	(6.65)	(1.59)	(0.18)	(1.71)
10 (High)	1.85	0.47	1.93	0.41	0.43	0.50
	(6.72)	(6.61)	(7.31)	(5.78)	(0.46)	(1.96)
High–Low	1.21	1.22	1.16	1.11	1.30	1.36
	(10.42)	(8.96)	(9.37)	(7.89)	(4.02)	(4.32)

(continued)

Table 12
Continued

Panel B: Returns on the liquidity shock portfolios for five decades in 1963–2010

	August 1963–July 1973		August 1973–July 1983		August 1983–July 1993		August 1993–July 2003		August 2003–December 2010	
Decile	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.23	−0.78	1.39	−0.54	0.38	−0.57	0.14	−1.04	0.39	−0.59
	(0.34)	(−6.19)	(2.27)	(−3.08)	(0.73)	(−7.01)	(0.28)	(−4.66)	(0.53)	(−3.65)
2	0.22	−0.66	1.32	−0.27	0.77	−0.32	0.45	−0.81	0.87	−0.08
	(0.39)	(−5.43)	(2.35)	(−1.53)	(1.50)	(−2.86)	(0.81)	(−3.35)	(1.23)	(−0.51)
3	0.36	−0.46	1.46	0.04	1.20	−0.04	0.87	−0.26	0.76	−0.14
	(0.63)	(−3.27)	(2.76)	(0.27)	(2.55)	(−0.26)	(1.89)	(−0.97)	(1.09)	(−1.01)
4	0.53	−0.30	1.27	−0.13	1.36	0.16	1.01	−0.08	1.01	0.12
	(0.94)	(−2.47)	(2.39)	(−1.26)	(3.17)	(1.11)	(2.52)	(−0.38)	(1.51)	(0.99)
5	0.88	0.06	1.36	−0.02	1.21	0.07	1.02	−0.04	0.86	−0.05
	(1.68)	(0.77)	(2.42)	(−0.23)	(2.81)	(0.46)	(2.48)	(−0.26)	(1.15)	(−0.34)
6	0.70	−0.14	1.49	0.08	1.18	0.10	0.97	−0.11	0.98	0.07
	(1.35)	(−1.95)	(2.66)	(0.66)	(2.86)	(1.11)	(2.43)	(−0.78)	(1.37)	(0.64)
7	1.08	0.20	1.75	0.33	1.19	0.11	1.00	−0.10	0.84	−0.01
	(2.17)	(2.22)	(3.16)	(2.17)	(2.71)	(1.32)	(2.39)	(−0.70)	(1.30)	(−0.08)
8	1.07	0.13	1.88	0.28	1.15	0.17	1.02	−0.11	0.96	0.06
	(2.10)	(1.31)	(3.12)	(1.80)	(2.48)	(1.63)	(2.14)	(−0.74)	(1.46)	(0.56)
9	1.16	0.21	2.22	0.46	1.01	0.08	1.23	0.06	0.98	0.09
	(1.97)	(1.64)	(3.55)	(2.67)	(2.08)	(0.92)	(2.52)	(0.56)	(1.60)	(0.74)
10 (High)	1.64	0.54	2.48	0.41	1.34	0.40	1.89	0.84	0.94	0.08
	(2.23)	(3.78)	(3.77)	(2.22)	(2.56)	(4.77)	(3.80)	(5.31)	(1.47)	(0.52)
High–Low	1.41	1.32	1.09	0.95	0.96	0.96	1.75	1.88	0.55	0.67
	(6.30)	(6.09)	(4.58)	(2.87)	(8.21)	(8.55)	(4.96)	(6.21)	(2.06)	(2.94)

Each month, stocks are sorted into 10 decile portfolios based on liquidity shock (LIQU), defined as the negative Amihud (2002) illiquidity measure, demeaned using the past 12-month illiquidity as the mean. This table reports the average monthly returns in month $t+1$ and the Fama-French (1993) alphas for each LIQU portfolio. The last row shows the differences in monthly returns between high- and low-LIQU decile portfolios and the alphas. In Panel A, column "Non-crisis period" covers the period from August 1963 to December 2010 and excludes the financial crisis period, July 2007–June 2009; the "expansionary" and "recessionary" periods are based on the NBER business cycle periods. Panel B reports the results 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.

Hvidkjaer (2006, 2008) finds that stocks with a high level of sell-initiated small-trade volume tend to outperform those with a high level of buy-initiated small-trade volume, suggesting that stocks favored by retail investors experience overshooting in the short term that result in subsequent reversals. One possibility is that stocks' increased liquidity is driven by increased selling by retail investors, which is followed by high returns in the subsequent months as the sells reverse out. This explanation is, however, unlikely as the Hvidkjaer mechanism leads to return reversals (price overshooting), while we observe return continuations (underreaction). To account for the effect of small-trade order flows, we follow Hvidkjaer (2008) and construct the signed small-trade turnover (SSTT) variable that is defined as the small-trade buy-initiated turnover minus the small-trade sell-initiated turnover, measured over the past 1 through 24 months.[33] It turns out that the Hvidkjaer variables have a very low correlation coefficient with our liquidity shock measures, ranging from -0.1% to -3.5%. We formally control for the Hvidkjaer variables using bivariate portfolio sorts and by including them as additional control variables in Fama-MacBeth regressions.

For month t, we sort common stocks into quintiles based on SSTT_J ($J=1$, 3, 6, 12, and 24); then within each STTT_J quintile, we further sort stocks into quintile portfolios of liquidity shock. Panel A of Table 13 reports the one-month-ahead returns and return differentials, averaged across the five control groups for the same liquidity shock quintile. Panels A1, A2, and A3 correspond to liquidity shock measures LIQU, SPRDU, and LIQCU, respectively. Our results show that, regardless of the horizon used to measure SSTT, controlling for SSTT does not affect the economic magnitude or the statistical significance of liquidity shocks' predictive power for future returns. The return differences between high- and low-liquidity shock portfolios and their corresponding Fama-French alphas are in the range of 77 and 129 basis points per month, and they are all significant at the 1% level.

We further run Fama-MacBeth predictive regressions of one-month-ahead returns on liquidity shock and SSTT_J, including all the other control variables listed in Table 6. Specifications (1) and (2) control for the GKM dummy variables (GKM_H and GKM_L) and the abnormal dollar trading volume (VOLDU), respectively. Panel B of Table 13 reports the average slope coefficients of liquidity shock and SSTT.[34] The results indicate that the average slope coefficients of liquidity shock measures remain positive and highly significant, and are similar in magnitude to those reported in Table 6. Consistent with Hvidkjaer (2008), the average slope coefficients of SSTT are always negative and are mostly significant for aggregate turnover over 3- to 12-month periods. Overall, the results of conditional bivariate sorts and Fama-MacBeth

[33] We provide a detailed description of the SSTT variables in the Appendix.

[34] For brevity, we suppress the average slope coefficients of the other control variables. They are available upon request.

cross-sectional regressions confirm that the predictive ability of liquidity shock is not driven by the effect of the signed small-trade turnover.

It could be argued that a liquidity shock can lead to a "flight to liquidity"—that is, 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 does lend support to investors' motive to dump their less liquid assets and move to more liquid assets.

Table 13
Controlling for the signed small-trade turnover

Panel A: Conditional bivariate sorts

Quintile	1-month SSTT	3-month SSTT	6-month SSTT	12-month SSTT	24-month SSTT
		Panel A1. Liquidity shock measured by LIQU			
1 (Low)	0.34	0.33	0.31	0.26	0.46
2	0.88	0.91	0.90	0.90	0.97
3	0.98	0.99	1.01	1.01	1.13
4	1.24	1.24	1.25	1.20	1.29
5 (High)	1.49	1.49	1.46	1.36	1.48
High–Low	1.15	1.15	1.14	1.10	1.02
	(4.25)	(4.08)	(4.30)	(4.23)	(3.48)
Alpha	1.29	1.28	1.26	1.23	1.17
	(5.67)	(5.33)	(5.62)	(5.51)	(4.83)
		Panel A2. Liquidity shock measured by SPRDU			
1 (Low)	0.43	0.46	0.44	0.41	0.48
2	0.74	0.73	0.74	0.72	0.83
3	0.96	0.95	0.95	0.98	1.10
4	1.12	1.10	1.09	1.09	1.14
5 (High)	1.37	1.35	1.32	1.18	1.32
High–Low	0.94	0.89	0.88	0.77	0.84
	(4.29)	(4.21)	(4.34)	(4.00)	(4.17)
Alpha	0.93	0.95	0.94	0.85	0.96
	(5.09)	(4.72)	(4.99)	(4.58)	(4.94)
		Panel A3. Liquidity shock measured by LIQCU			
1 (Low)	0.43	0.42	0.42	0.39	0.42
2	0.75	0.75	0.75	0.75	0.81
3	1.04	1.09	1.10	1.09	1.19
4	1.23	1.23	1.21	1.10	1.18
5 (High)	1.26	1.25	1.23	1.17	1.29
High–Low	0.83	0.83	0.81	0.78	0.87
	(4.68)	(4.10)	(4.01)	(3.95)	(3.70)
Alpha	1.12	0.98	0.95	0.95	1.04
	(5.31)	(4.43)	(4.21)	(4.28)	(4.06)

(*continued*)

Table 13
Continued

Panel B: Monthly Fama-MacBeth regressions

	1-month SSTT		3-month SSTT		6-month SSTT		12-month SSTT		24-month SSTT	
Variable	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel B1. Liquidity shock measured by LIQU										
LIQU	0.227	0.206	0.220	0.199	0.267	0.244	0.276	0.247	0.232	0.205
	(3.76)	(3.41)	(3.92)	(3.55)	(4.01)	(3.62)	(3.44)	(3.07)	(3.69)	(3.27)
SSTT	−14.635	−17.713	−12.217	−13.110	−7.355	−7.355	−3.458	−3.254	−2.500	−2.334
	(−1.76)	(−2.07)	(−3.47)	(−3.63)	(−3.20)	(−3.19)	(−2.39)	(−2.24)	(−2.08)	(−1.95)
Panel B2. Liquidity shock measured by SPRDU										
SPRDU	0.655	0.565	0.618	0.527	0.672	0.570	0.556	0.451	0.623	0.536
	(5.98)	(5.16)	(5.33)	(4.59)	(5.48)	(4.68)	(4.45)	(3.58)	(4.93)	(4.25)
SSTT	−10.087	−12.231	−10.787	−11.692	−6.990	−7.029	−4.424	−4.267	−2.318	−2.187
	(−0.91)	(−1.11)	(−2.46)	(−2.60)	(−2.88)	(−2.87)	(−2.71)	(−2.62)	(−2.00)	(−1.89)
Panel B3. Liquidity shock measured by LIQCU										
LIQCU	0.156	0.127	0.163	0.136	0.159	0.131	0.142	0.112	0.165	0.140
	(4.32)	(3.11)	(4.42)	(3.21)	(4.53)	(3.27)	(3.99)	(2.75)	(4.28)	(3.23)
SSTT	−14.972	−17.581	−12.648	−13.418	−7.610	−7.539	−3.536	−3.318	−2.531	−2.361
	(−1.75)	(−2.02)	(−3.48)	(−3.63)	(−3.26)	(−3.24)	(−2.43)	(−2.27)	(−2.13)	(−1.99)

Panel A of this table reports one-month-ahead average returns and return differences between high- and low-liquidity shock quintile portfolios and the Fama-French (1993) alphas after controlling for the signed small-trade turnover (SSTT). Panel B reports the average slope coefficients of liquidity shock and SSTT from the Fama-MacBeth cross-sectional regressions of one-month-ahead excess stock returns on liquidity shock and SSTT, including all the other control variables listed in Table 6. Specifications (1) and (2) control for the GKM dummy variables (GKM_H and GKM_L) and the abnormal dollar trading volume (VOLDU), respectively. SSTT is defined as the small-trade buy-initiated turnover minus the small-trade sell-initiated turnover, measured over the past 1 through 24 months. Liquidity shock is measured by LIQU in Panels A1 and B1, SPRDU in Panels A2 and B2, and LIQCU in Panels A3 and B3. Newey-West t-statistics are reported in parentheses.

Another potential mechanism driving our main findings is that 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. In contrast, 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 link between liquidity shocks and future stock returns during crisis periods. However, it is not clear whether this effect should be there during normal periods. Given that our finding of a positive relation between liquidity shocks and future stock returns is equally strong for non-crisis periods as well as recessionary and expansionary periods, it seems that the proposed story cannot fully explain our findings.

Can the positive relation 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 shocks and should have factored it into prices, leaving no return predictability. Thus, correlated liquidity shocks should not be able to predict future returns.

Liquidity shocks can be triggered by public information releases such as earnings announcements, company events such as stock splits and share buybacks, the return performance of stocks, and sensitivity of stocks to changes in market liquidity, or due to concerns about trading against informed traders in times of heightened uncertainty. Can liquidity shocks' return predictability be a manifestation of effects of these other events? Generally speaking, if markets are rational and react to information promptly, these other value-relevant shocks 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 and past earnings surprises, as well as an extensive list of other variables, suggesting that these other factors alone, without market frictions, can not explain our findings.

6. 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 illiquidity is positively priced in the cross-section of expected returns and that liquidity shocks have persistent effects, one would expect that negative liquidity shocks lead to higher future returns if the stock market reacts immediately and to the full extent of the increased illiquidity premium.

On the contrary, we find a surprising positive relation between stock-level liquidity shocks and future returns: decile portfolios that long stocks with positive liquidity shocks and short stocks with negative liquidity shocks generate a raw and risk-adjusted return of 0.70% to 1.20% per month. This relation is economically and statistically significant and robust across alternative measures of liquidity shocks and after controlling for various risk factors and stock characteristics such as beta, size, book-to-market, momentum, short-term reversal, co-skewness, idiosyncratic volatility, maximum daily return, analyst dispersion, level and volatility of illiquidity, exposures to systematic liquidity factors, unexpected earnings, volatility shocks, abnormal dollar trading volume, and signed small-trade turnover. The strong predictive power of liquidity shocks remains intact for various subsample periods, as well as across recessionary and expansionary periods.

We show that negative liquidity shocks not only lead to lower contemporaneous returns, but also continue to predict negative returns for up to seven months in the future. This evidence suggests that the stock market underreacts to stock-level liquidity shocks.

We explore two potential driving forces of this underreaction: investor inattention and illiquidity. We find that the predictive power of liquidity shocks for future returns is stronger among stocks that receive less investor attention (small stocks and stocks with low analyst coverage and low institutional holdings) as well as among less liquid stocks. While both mechanisms are significant in explaining one-month-ahead return predictability of liquidity shocks, the investor inattention mechanism is stronger in predicting two- to four-month-ahead returns.

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 on the stock market's underreaction to stock-level liquidity shocks.

For future work, it might be interesting to focus on concrete cases of liquidity shocks and study the market's reactions to these particular episodes in an event study setting. For example, the stock market's underreaction to stock splits and the associated liquidity changes can potentially explain the post-split price drift found in Ikenberry, Rankine, and Stice (1996) and Desai and Jain (1997). Another interesting question for future analysis is to identify the exact propagation mechanism of the securities market's underreaction to liquidity shocks. Given that securities dealers (or designated market makers) are liquidity providers, why wouldn't they be able to react promptly to liquidity shocks by changing their quotes? The recent literature suggests that dealers themselves are subject to limited attention (Corwin and Coughenour 2008; Boulatov et al. 2009; Chakrabarty and Moulton 2012). Hence, it would be interesting to explore how liquidity shocks affect dealers' attention allocation and quoting behavior, and as a result, how order flow and securities prices adjust in response to shocks.

Appendix

This appendix provides detailed descriptions of how we construct our control variables. Unless otherwise stated, we measure all variables at the end of portfolio formation month (that is, month t) and require a minimum of 15 daily observations for all variables computed monthly from daily data.

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 (minimum of 24 months):

$$R_{i,t}-R_{f,t}=\alpha_i+\beta_i^1\left(R_{m,t}-R_{f,t}\right)+\beta_i^2\left(R_{m,t-1}-R_{f,t-1}\right)+\varepsilon_{i,t}, \tag{A1}$$

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 stock'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 stock's size (LNME) is 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, 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 the end of December of $t-1$. Depending on availability, the redemption, liquidation, or par value (in that order) is used as 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 stock'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 (minimum of 24 months):

$$R_{i,t}-R_{f,t}=\alpha_i+\beta_i\left(R_{m,t}-R_{f,t}\right)+\gamma_i\left(R_{m,t}-R_{f,t}\right)^2+\varepsilon_{i,t}, \tag{A2}$$

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 and colleagues (2006), the monthly idiosyncratic volatility of stock i (IVOL) is computed as the standard deviation of the residuals from the regression:

$$R_{i,d}-R_{f,d}=\alpha_i+\beta_i\left(R_{m,d}-R_{f,d}\right)+\gamma_i SMB_d+\varphi_i HML_d+\varepsilon_{i,d}, \tag{A3}$$

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 stock's extreme positive return (MAX) is defined as its maximum daily return in each 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.

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. To control for this effect, we follow Ball and Brown (1968) and Bernard and Thomas (1989, 1990) and define stock i's unexpected EPS (UE) in calendar quarter q of earnings announcement as:

$$UE_{i,q}=EPS_{i,q}-EPS_{i,q-4}, \tag{A4}$$

where $EPS_{i,q}$ and $EPS_{i,q-4}$ are the stock's basic EPS, excluding extraordinary items in quarters q and $q-4$, respectively. The stock's standardized unexpected earnings in quarter q (SUE_q) is UE_q scaled by its standard deviation over the past eight quarters (with a minimum of four UE observations available).

Since a stock's liquidity and trading volume are 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 on the last but second trading day in the portfolio formation month relative to daily dollar trading volume over the prior 49 trading days. We then create two volume premium dummy variables: the high-volume dummy variable (GKM_H) is 1 if a stock belongs to the high-volume group and zero otherwise; the low-volume dummy variable (GKM_L) is equal to 1 if a stock resides in the low-volume portfolio and zero otherwise. Hence, stock i in month t belongs to one of the three groups, GKM_H, GKM_L, and GKM_M, indicating that the stock does not experience abnormally high or low dollar volume. We further construct a continuous variable for abnormal dollar volume (VOLDU) in the same fashion as we define the liquidity shock. That is, we subtract monthly dollar volume by its past 12-month average.

We also control for a variety of liquidity-based variables. 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 illiquidity measure in a month scaled by the monthly Amihud illiquidity measure.

Following Pastor and Stambaugh (2003), the stock'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 24 months are available):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \varepsilon_{i,t}, \tag{A5}$$

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).

Following Acharya and Pedersen (2005) at the end of year $k-1$, we sort common stocks listed on NYSE, AMEX, and NASDAQ into 25 groups based on the average daily Amihud (2002) illiquidity ratio in year $k-1$ (with at least 100 daily ratios available) using the NYSE illiquidity breakpoints. We estimate the four betas proposed in Acharya and Pedersen (2005) that capture different aspects of a security's systematic risk in a world where trading costs vary randomly over time:

$$\beta_p^1 = \frac{Cov\left(r_{p,t}, r_{m,t}\right)}{Var\left(r_{m,t} - cu_{m,t}\right)}, \tag{A6}$$

$$\beta_p^2 = \frac{Cov\left(cu_{p,t}, cu_{m,t}\right)}{Var\left(r_{m,t} - cu_{m,t}\right)}, \tag{A7}$$

$$\beta_p^3 = \frac{Cov\left(r_{p,t}, cu_{m,t}\right)}{Var\left(r_{m,t} - cu_{m,t}\right)}, \tag{A8}$$

$$\beta_p^4 = \frac{Cov\left(cu_{p,t}, rm_{m,t}\right)}{Var\left(r_{m,t} - cu_{m,t}\right)}, \tag{A9}$$

where r_p and r_m are, respectively, the monthly excess returns for portfolio p and the market portfolio proxied by the CRSP equal-weighted index; cu_p and cu_m are the monthly innovations in illiquidity for portfolio p and the market, respectively. For each month t, we normalize the monthly Amihud (2002) illiquidity measures in months t to $t-2$ for stock i (denoted $c_{i,t}$, $c_{i,t-1|t}$, and $c_{i,t-2|t}$, respectively) by

$$c_{i,t} = min\left(0.25 + 0.3 ILLIQ_{i,t} P_{m,t-1}, 30\right), \tag{A10}$$

$$c_{i,t-1} = min\left(0.25 + 0.3 ILLIQ_{i,t-1} P_{m,t-1}, 30\right), \tag{A11}$$

$$c_{i,t-2} = min\left(0.25 + 0.3 ILLIQ_{i,t-2} P_{m,t-1}, 30\right), \tag{A12}$$

where $P_{m,t-1}$ is the ratio of the capitalization of the market portfolio at the end of month $t-1$ to that as of the end of July 1962. We then calculate the illiquidity measures in months t to $t-2$ for each illiquidity portfolio (denoted $c_{p,t}$, $c_{p,t-1|t}$, and $c_{p,t-2|t}$, respectively) by averaging the corresponding normalized illiquidity measures for each stock in the portfolio:

$$c_{p,t} = \frac{1}{N}\sum_{t=1}^{T} c_{i,t}, \tag{A13}$$

$$c_{p,t-1|t} = \frac{1}{N}\sum_{t=1}^{T} c_{i,t-1|t}, \tag{A14}$$

$$c_{p,t-2|t} = \frac{1}{N}\sum_{t=1}^{T} c_{i,t-2|t}. \tag{A15}$$

The illiquidity measures in months t to $t-2$ for the market (denoted $c_{m,t}$, $c_{m,t-1|t}$, and $c_{m,t-2|t}$, respectively) are calculated similarly by averaging the corresponding normalized illiquidity measures for NYSE/AMEX common stocks.

The liquidity innovations in month t for portfolio p ($cu_{p,t}$) and the market ($cm_{p,t}$) are defined as the residuals of the AR(2) model estimated based on a 60-month rolling sample with a minimum of 24 observations and updated on a monthly basis:

$$c_{p/m,t} = a_0 + a_1 c_{p/m,t-1|t} + a_2 c_{p/m,t-2|t} + \varepsilon_{p/m,t}, \tag{A16}$$

$$cu_{p/m,t} \equiv \varepsilon_{p/m,t}. \tag{A17}$$

For each month t, the four factor loadings of stock i (denoted $\beta^1_{i,t}$, $\beta^2_{i,t}$, $\beta^3_{i,t}$, and $\beta^4_{i,t}$) are, respectively, set to $\beta^1_{p,t}$, $\beta^2_{p,t}$, $\beta^3_{p,t}$, and $\beta^4_{p,t}$ of the illiquidity portfolio to which the stock belongs in the month.

We further control for the pricing effects of the illiquidity risk factor of Sadka (2006). We download from Ronnie Sadka's webpage the time-series of the monthly fixed and variable components of the illiquidity factor covering the period from April 1984 to December 2010. For each month, a stock's illiquidity risk loadings on the fixed and the variable components (denoted SADKAF and SADKAV, respectively) are estimated using monthly return data over the prior 60 months with a minimum of 24 monthly observations available after controlling for the monthly market, size, and book-to-market factors of Fama and French (1993):

$$R_{i,t} - R_{f,t} = \alpha_i + \lambda_1 FIX_t + \lambda_2 VAR_t + \beta_i \left(R_{m,t} - R_{f,t}\right) + \gamma_i SMB_t + \varphi_i HML_t + \varepsilon_{i,t}, \tag{A18}$$

where FIX and VAR are the fixed and variable components of the Sadka liquidity factor.

In Section 3, 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) stock size (LNME); (ii) analyst coverage (CVRG), computed as the natural logarithm of the number of analysts covering the stock in the portfolio formation month; and (iii) institutional holdings (INST), defined as quarterly institutional ownership as of the portfolio formation month.

In Section 5, to ensure that our liquidity shock measures are not picking up the effect of small trade order flows, we control for the variables originally introduced by Hvidkjaer (2008). Each trade from the TAQ database covering the period of 1993–2010 is identified as buy- or sell-initiated using the procedure described in Lee and Ready (1991). We sort stocks into quintile portfolios based on the NYSE/AMEX size breakpoints. The small-trade cutoff for each size quintile is calculated as the ratio of a dollar cutoff to the share price at the end of the prior month rounded up to the nearest hundred round-lot, where the dollar cutoffs are, respectively, \$4,800, \$7,300, \$10,300, and \$16,400 for the smallest to the largest size portfolios. The monthly small-trade buy-initiated turnover is calculated as the ratio of the small-trade buy-volume in a month to the number of shares outstanding. The monthly small-trade sell-initiated turnover is calculated similarly. At the end of each portfolio formation month (that is, month t), the small-trade buy- and sell-initiated turnover are then summed over the prior J months, where $J = 1$, 3, 6, 12, and 24. For each J, the signed small-trade turnover (SSTT$_J$) is the difference between the corresponding summed small-trade buy-initiated turnover and the summed small-trade sell-initiated turnover.

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