Liquidity components: Commonality in liquidity, underreaction, and equity returns☆

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ABSTRACT

I decompose firm-specific monthly-varying illiquidity into three components: (i) alpha, (ii) systematic, and (iii) idiosyncratic. Investors demand a premium to hold stocks with high systematic illiquidity. However, the systematic illiquidity premium disappears when very small stocks are excluded. On the other hand, investors tend to underreact to idiosyncratic (il)liquidity. Hence, stocks with high (low) idiosyncratic liquidity generate positive (negative) future risk-adjusted returns. More specifically, stocks in the highest idiosyncratic liquidity quintile generate 7% more annualized risk-adjusted return compared to stocks in the lowest idiosyncratic liquidity quintile.

1. Introduction

Liquidity refers to the ease and speed that a security can be traded in the financial market without incurring a high transaction cost or adverse price impact. Illiquid stocks are considered difficult to sell and may give rise to significant losses when the investors cannot sell when they want to. Amihud and Mendelson (1986), introducing the bid–ask spread as a proxy for illiquidity, show that investors demand extra compensation to hold illiquid assets; thus, illiquid stocks generate high future returns. Subsequently, Brennan and Subrahmanyam (1996), Brennan et al. (1998), Datar et al. (1998), Chordia et al. (2001a), Amihud (2002), and Hasbrouck (2009) document the cross-sectional relationship between the level of illiquidity and expected stock returns. On the other hand, there are numerous studies that test the predictive power of illiquidity risk on expected stock returns (Akbas et al., 2011; Chordia et al., 2000; Lo and Wang, 2000; Huberman and Halka, 2001; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006; Korajczyk and Sadka, 2008). As opposed to the illiquidity premium, Bali et al. (2014) introduce a measure of stock-level liquidity shocks and show that the stock market underreacts to liquidity shocks. Hence, strategies formed by sorting on liquidity shocks generate positive and significant risk-adjusted returns.

Adding to the literature, in this paper, I decompose firm-level monthly-varying illiquidity into three components: (i) alpha, (ii) systematic, and (iii) idiosyncratic. Then, I investigate the importance of each component in the cross-sectional pricing of individual stocks. While introducing illiquidity components, I provide evidence to (i) commonality in liquidity and (ii) underreaction to idiosyncratic liquidity.

Chordia et al. (2000) introduce commonality in liquidity, which refers to the proposition that an individual firm's liquidity is at least partly determined by market-wide factors and it arises due to publicly available market-wide information flow.[1] Consistently, Huberman and Halka (2001) document a time-varying systematic component of liquidity. There are several demand-side driven explanations to commonality in liquidity: correlated trading behaviour of institutional investors (Kamara et al., 2008; Koch et al., 2009), investors' weak incentives to trade in individual securities (Morck et al., 2000), and investor sentiment (Huberman and Halka, 2001). On the supply side, Coughenour and Saad (2004) and Hameed et al. (2010) argue that financial intermediaries' funding constraints contribute to commonality in liquidity. Adding to the U.S.-based evidence, Karolyi et al. (2012) document commonality in liquidity for 40 different equity markets.

According to Kahneman's 1973 attention theory, attention is a scarce cognitive resource. Peng and Xiong (2006) documents that investors tend to allocate more attention to market-wide information than firm-specific information.[2] In an extreme case, attention-constrained investors exclusively concentrate on common factors and ignore all firm-specific information. Hence, firm-level systematic and idiosyncratic liquidity components might have distinct cross-sectional pricing implications. If the market-wide illiquidity (liquidity) increases (decreases), investors might face severe difficulty selling stocks with high sensitivity to market-wide illiquidity. Hence, risk-averse investors are expected to demand compensation to hold stocks whose liquidity is highly sensitive to market-wide liquidity. On the other hand, the idiosyncratic liquidity component is more prone to mispricing. As a result, there might be an insignificant or negative (positive) cross-sectional relationship between firm-level idiosyncratic illiquidity (liquidity) and subsequent stock returns. Providing commonality in liquidity and underreaction explanations, in this paper, I investigate the cross-sectional pricing of (il)liquidity components.

By taking market capitalization-weighted averages of firm-specific illiquidity measures of all available firms in the CRSP universe, I generate a monthly-varying market-wide illiquidity measure.[3] I decompose each stock's monthly illiquidity into intercept, systematic, and idiosyncratic components by 60-month rolling regressions of firm-specific monthly-varying illiquidity on the market-wide illiquidity. The intercept term can be interpreted as expected illiquidity, whereas systematic (il)liquidity can be considered as the comovement of a stock's liquidity with the market liquidity. On the other hand, idiosyncratic (il)liquidity is the component that cannot be explained by market-wide liquidity. As it is a commonly used proxy, I use the illiquidity measure of Amihud (2002) to quantify the market-wide and firm-specific (il)liquidity.[4] Then, I provide the out-of-sample performance of ex-ante measures of firm-specific intercept, systematic, and idiosyncratic (il)liquidity measures in predicting the cross-sectional variation in stock returns.

My first set of results documents a positive but relatively weak relationship between the intercept and systematic illiquidity components and one-month-ahead stock returns. More specifically, both equal-weighted portfolio sorts and firm-level cross-sectional regressions document a positive and significant relationship between the intercept term, systematic illiquidity, and one-month-ahead stock returns. However, the illiquidity premium disappears when larger firms have larger weights in the portfolios (value-weighted portfolios) and when small stocks are excluded.

Subsequently, as the paper's main contribution, I present a positive (negative) and significant cross-sectional relationship between idiosyncratic liquidity (illiquidity) and future stock returns. First, I sort individual stocks into quintile portfolios based on their idiosyncratic liquidity measure during the previous month and examine the monthly returns on the resulting portfolios from January 1969 to December 2018. While testing against various risk factor models with excess market returns, and size, book-to-market, momentum, profitability, investment, and liquidity factors of Fama and French (1993, 2015), Carhart (1997), Pastor and Stambaugh (2003), and Hou et al. (2015), a high-low idiosyncratic liquidity strategy, in which an investor takes a long position in high idiosyncratic liquidity stocks and a short position in low idiosyncratic liquidity stocks, generates significantly positive contemporaneous and one-month-ahead risk-adjusted returns. Specifically, stocks in the highest idiosyncratic liquidity quintile produce around 7% more value-weighted risk-adjusted annualized return than stocks in the lowest idiosyncratic liquidity quintile. The significant alpha spread between the extreme quintile portfolios is due to both the outperformance by high idiosyncratic liquidity stocks and the underperformance by low idiosyncratic liquidity stocks.

Next, I examine the cross-sectional pricing of idiosyncratic liquidity while accounting for various firm-specific characteristics and risk factors. Firm-level cross-sectional Fama and MacBeth (1973) regressions verify that idiosyncratic liquidity significantly predicts subsequent stock returns while controlling for various firm-level characteristics and risk factors, such as market beta, market capitalization, and book-to-market ratio (Fama and French, 1992, 1993), intermediate-term momentum (Jegadeesh and Titman, 1993), short-term reversal (Jegadeesh, 1990), idiosyncratic volatility (Ang et al., 2006), profitability and investment measures (Fama and French, 2015; Hou et al., 2015), and MAX, the demand for lottery-type stocks proxy introduced by Bali et al. (2011). In addition to the risk factors and stock characteristics, liquidity related control variables, such as standardized unexpected earnings (Ball and Brown, 1968; Bernard and Thomas, 1989, 1990), standard deviation of turnover (Chordia et al., 2001b), coefficient of variation in Amihud's illiquidity measure (Akbas et al., 2011), stock's liquidity exposure to innovations in the aggregate liquidity factor (Pastor and Stambaugh, 2003), covariances of a stock's return and liquidity with the market return and liquidity (Acharya and Pedersen, 2005), a stock's illiquidity risk on the fixed and variable components of Sadka's 2006 liquidity factor, and liquidity shocks measure of Bali et al. (2014) are added to the regressions.

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[1] Chordia et al. (2000) state that stock-level liquidity not only comoves with market-wide liquidity but also with industry-wide liquidity. As a robustness test, I estimate firm-level monthly-varying idiosyncratic liquidity while accounting for both market- and industry-wide liquidity.

[2] Chen et al. (2018) show that investors pay more attention to macroeconomic news than firm-specific news, such as earnings announcements.

[3] As explained in the upcoming section, both stock-level illiquidity and market-wide illiquidity measures are detrended to avoid non-stationarity issues.

[4] While I focus on Amihud's (2002) illiquidity measure to construct (il)liquidity components, the results are robust to the effective bid–ask spread measure of Corwin and Schultz (2012).

Both portfolio-level analyses and firm-level cross-section regressions document that idiosyncratic liquidity continues to predict future stock returns up to four months. The results suggest that investors tend to underreact both to positive and negative idiosyncratic liquidity components. Hence, stocks with positive (negative) idiosyncratic liquidity tend to generate positive (negative) abnormal returns for consecutive periods. Investor inattention, costly arbitrage, and investor sentiment are potential mechanisms that contribute to the underreaction to idiosyncratic liquidity.

Finally, I investigate the robustness of the findings. First, I estimate firm-specific monthly-varying idiosyncratic liquidity measure through rolling regressions of firm-specific Amihud's illiquidity (2002) measure on the equal-weighted market-wide illiquidity measure. Second, I estimate idiosyncratic liquidity through bivariate regressions of firm-specific monthly-varying illiquidity on value-weighted market-wide and industry-wide illiquidity. Third, I compute idiosyncratic liquidity through an alternative measure of liquidity, the volume-weighted effective relative spread. The results suggest that the cross-sectional relation between idiosyncratic liquidity and future stock returns is robust to various specifications and illiquidity measures.

The paper is organized as follows. In Section 2, I describe the data and introduce the variable definitions. Section 3 presents the empirical results. Concluding remarks are in Section 4.

2. Data and variable definitions

The stock sample includes all common stocks traded on the NYSE, Amex, and Nasdaq from January 1964 to December 2018. The daily and monthly returns, and the volume data are from the Center for Research in Security Prices (CRSP). Accounting variables are obtained from the merged CRSP-Compustat database. I require at least 24 monthly observations and 15 daily observations to be available for variables estimated using monthly data over the past 60 months and daily data over the past one month, respectively.

2.1. Liquidity components

I use the illiquidity (*ILLIQ*) measure proposed by Amihud (2002). Daily illiquidity is quantified as the ratio of daily absolute stock return scaled by its daily dollar trading volume. A stock's monthly illiquidity measure is computed as the average of its daily illiquidity within a month. I scale the Amihud illiquidity measure by 10^6. To decompose the firm-level monthly-varying illiquidity measure into components, I construct a market-wide illiquidity index by taking value-weighted averages of firm-specific Amihud (2002) illiquidity (*ILLIQ*) of all stocks in the CRSP universe:

$$Market - illiquidity_t = \sum_i Size - ratio_{i,t} * ILLIQ_{i,t}, \tag{1}$$

where the size ratio is equal to:

$$Size - ratio_{i,t} = \frac{Market - capitalization_{i,t}}{\sum_i Market - Capitalization_{i,t}}. \tag{2}$$

In Fig. 1, I plot market-wide illiquidity from January 1964 to December 2018.[5] The upward spikes indicate increasing levels of market-wide illiquidity. Many of the spikes take place during market declines, consistent with liquidity measures developed by Chordia et al. (2001a), Jones (2002), and Pastor and Stambaugh (2003).

Panel A of Table 1 provides the time-series descriptive statistics for the value-weighted market-wide illiquidity and several macroeconomic and financial variables, such as the investor sentiment index (Baker and Wurgler, 2007), one-month Treasury rate, one-month-lagged excess stock market return, and one-month-ahead (forward-looking) uncertainty index of Jurado et al. (2015). Consistent with Fig. 1, stock market illiquidity reached historic highs (0.978) throughout the 1990–1991 recessionary period. On the other hand, the stock market exhibited the highest (lowest) (il)liquidity levels between 2004 and 2007 and the period following the Great Recession.

Panel B of Table 1 reports the time series correlation coefficients for the market-wide illiquidity and the variables mentioned above. Baker and Stein (2004) argue that market-wide liquidity can be an investor sentiment indicator. Consistently, Panel B shows a negative (positive) correlation between market-wide illiquidity (liquidity) and investor sentiment index. In addition, consistent with Chordia et al. (2000), market-wide illiquidity is strongly correlated with the short-term interest rate (one-month Treasury rate), past market returns (one-month-lagged excess stock market return), and economic uncertainty. Hameed et al. (2010) find that negative market returns decrease stock market liquidity, especially during tightened funding market conditions. Consistently, Panel B documents a negative correlation between market-wide illiquidity and past market return. In addition, investors tend to liquidate stocks less when they face high economic uncertainty.

As Fig. 1 suggests, stock market liquidity has improved over the last decades, which may suggest a potential non-stationarity problem. Chordia et al. (2000) argue that time-series regressions on liquidity changes rather than levels solve the non-stationarity issue. Hence, I detrend market-wide illiquidity by subtracting its four-month moving average. In Fig. 2, I plot detrended market-wide illiquidity from 1964 to 2018. To ensure avoiding a potential non-stationarity problem, I test for stationarity of the detrended market-wide value by employing the (time series) augmented Dickey–Fuller test. The test rejects the null hypothesis of a unit root at any significance level.

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[5] This figure shows the value-weighted market-wide illiquidity measure where all stocks are included. However, when I decompose each stock's illiquidity into components, the stock-specific market-wide illiquidity measure excludes the stock's own illiquidity measure. Hence, each stock has different market-wide illiquidity exposures.
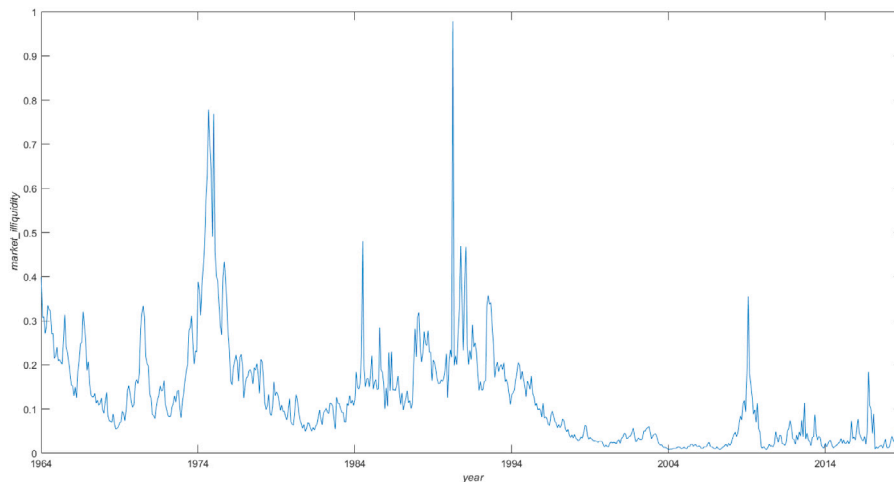
Fig. 1. Market-wide illiquidity.

Table 1
Descriptive statistics and correlation matrix.

	Panel A: Summary statistics					
	Mean	Min	25th Per	Median	75th Per	Max
Market Illiq	0.128	0.007	0.034	0.100	0.183	0.978
Illiq Change	−0.001	−0.209	−0.018	−0.001	0.014	0.783
Sentiment	0.023	−2.548	−0.445	0.002	0.536	2.422
Interest	0.003	0	0.001	0.004	0.005	0.013
Past Return	0.005	−0.232	−0.021	0.008	0.034	0.161
Uncertainty	0.620	0.511	0.572	0.603	0.655	0.929
	Panel B: Correlation matrix					
	Market Illiq	Illiq Change	Sentiment	Interest	Past Return	Uncertainty
Market Illiq	1	0.38	−0.32	0.35	−0.13	0.30
Illiq Change		1	0.08	0.05	−0.30	−0.01
Sentiment			1	0.22	−0.08	−0.15
Interest				1	−0.08	0.30
Past Return					1	−0.08
Uncertainty						1

Panel A reports the selected moments (mean, minimum, 25th percentile, median, 75th percentile, and maximum) of value-weighted market-wide illiquidity (Market Illiq), one-month-change in market-wide illiquidity (Illiq Change), investor sentiment index (Sentiment) of Baker and Wurgler (2007), one-month Treasury rate (Interest), one-month-lagged excess stock market return (Past Return), and one-month-ahead financial uncertainty index (Uncertainty) of Jurado et al. (2015). Panel B provides a time series correlation matrix.

While calculating the stock-specific market-wide illiquidity measure (Figs. 1 and 2 include all stocks in the CRSP universe), a stock's own illiquidity measure is excluded. Hence, the stock-level market-wide illiquidity exposure is formulated as:

$$Market - illiquidity_{i,t} = \sum_{-i} Size - ratio_{i,t} * ILLIQ_{i,t}. \tag{3}$$

Hence, each stock has a different market-wide illiquidity exposure. Then, I detrend each stock's own illiquidity and its market-wide illiquidity measures by subtracting four-month moving averages.[6] Using detrended illiquidity measures, I estimate firm-level monthly-varying illiquidity alpha, as well as systematic and idiosyncratic illiquidity measures from the univariate monthly rolling regressions of stock-specific detrended Amihud (2002) illiquidity on the detrended market-wide illiquidity over a 60-month fixed window[7]:

$$d - ILLIQ_{i,t} = \alpha_{i,t} + \beta_{i,t}^{Market} * d - Market - illiquidity_{i,t} + \epsilon_{i,t}. \tag{4}$$

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[6] To avoid a potential non-stationarity problem, I employ the (panel) Im-Pesaran-Shin test. The test rejects both null hypotheses that stock-level illiquidity and market-wide illiquidity measures have unit roots.

[7] Chordia et al. (2001b) estimate stocks' exposure to market-wide and industry-wide illiquidity movements (changes). As a robustness test, I estimate the firm-level illiquidity components through bivariate regressions of stock-level illiquidity on the market- and industry-wide illiquidity measures.
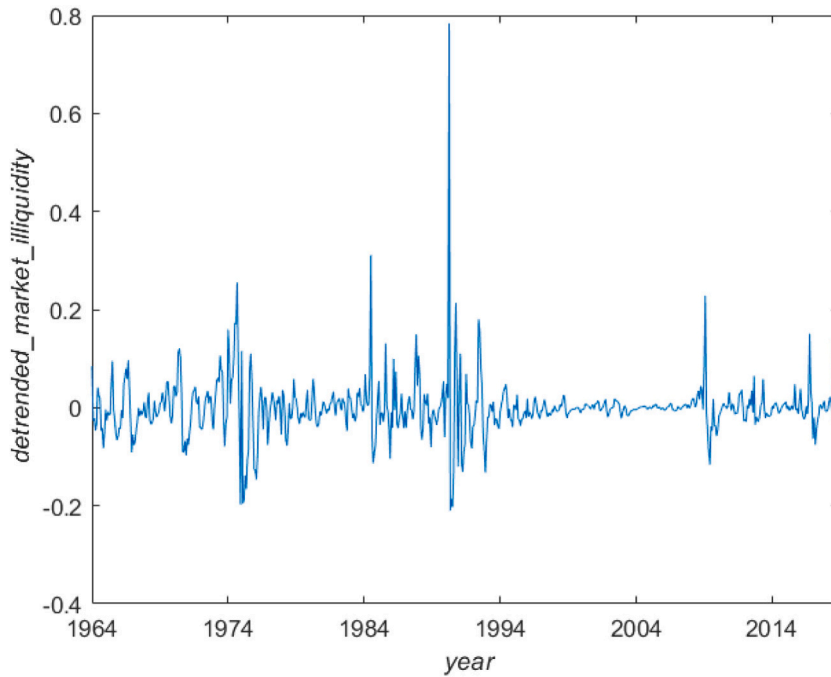
Fig. 2. Detrended market-wide illiquidity.

Table 2
Cross-sectional correlation matrix.

	Cross-sectional correlations						
	ILLIQ	d-ILLIQ	β	SYS-ILLIQ	$\beta * |MARKET|$	IDIO-LIQ	α_{ILLIQ}
ILLIQ	1	0.54	0.24	0.04	0.23	−0.47	0.37
d-ILLIQ		1	0.02	0.13	0.02	−0.89	0.07
β			1	−0.09	0.99	−0.03	0.15
SYS-ILLIQ				1	−0.09	0.11	−0.05
$\beta * |MARKET|$					1	−0.03	0.14
IDIO-LIQ						1	0.01
α_{ILLIQ}							1

This table reports time series averages of the monthly cross-sectional correlations between the stock-level illiquidity measures in the sample. The measures include stock-level Amihud illiquidity (2002) (ILLIQ), detrended stock-level illiquidity (d-ILLIQ), stock-level illiquidity beta estimated through equation (4) (β), systematic illiquidity (SYS-ILLIQ), illiquidity beta multiplied by absolute value of detrended market illiquidity ($\beta * |MARKET|$), idiosyncratic liquidity (IDIO-LIQ), and illiquidity alpha (α_{ILLIQ}). The sample covers the period from 1969 to 2018.

Illiquidity alpha (α_{ILLIQ}) is the intercept from the regression. Systematic illiquidity (*SYS-ILLIQ*) is quantified as $\beta_{i,t}^{Market}$ * $d - Market - illiquidity_{i,t}$, whereas idiosyncratic illiquidity (*IDIO-ILLIQ*) is equal to stock-level illiquidity (ILLIQ) minus α_{ILLIQ} minus SYS-ILLIQ. In other words, idiosyncratic illiquidity refers to the residuals from the rolling regressions. While systematic and idiosyncratic illiquidity refer to increasing (decreasing) levels of illiquidity (liquidity), I construct systematic (*SYS-LIQ*) and idiosyncratic liquidity (*IDIO-LIQ*) measures as the negative signs of systematic and idiosyncratic illiquidity measures. To illustrate, I compute the intercept, systematic, and idiosyncratic liquidity components over rolling regressions over a 60-month fixed window (from "*t-59*" to "*t*") and estimate their predictive power on one-month-ahead ("*t+1*") excess stock returns:

$$IDIO - LIQ = -(IDIO - ILLIQ). \tag{5}$$

Table 2 reports time series averages of the monthly cross-sectional correlations between the stock-level illiquidity measures. The measures are Amihud's 2002 illiquidity, detrended stock-level illiquidity, illiquidity beta, systematic illiquidity, and illiquidity beta multiplied by the absolute value of market-wide illiquidity, idiosyncratic liquidity, and illiquidity alpha. As expected, stock-level illiquidity is significantly correlated with detrended illiquidity. Illiquid stocks tend to have a high illiquidity beta, which means they are highly sensitive to the movements in market-wide illiquidity. Illiquid stocks have low (high) idiosyncratic (il)liquidity and high illiquidity alpha.

There is a moderate correlation between detrended illiquidity and systematic illiquidity ($\varphi = 0.13$). Idiosyncratic liquidity is negatively correlated with detrended illiquidity ($\varphi = -0.89$). By construction, liquidity beta is highly correlated with liquidity beta

multiplied by absolute value of detrended market-wide illiquidity.[8] There is a moderate correlation ($\varphi = 0.15$) between illiquidity beta and illiquidity alpha suggesting that stocks whose liquidity is highly sensitive to market-wide illiquidity tend to have high illiquidity alpha (expected illiquidity).

2.2. Return predictors and data

Following Fama and French (1992), I estimate individual stocks' market beta using monthly excess returns over the prior 60 months. Market capitalization (SIZE) is calculated as the stock's number of shares outstanding multiplied by its price per share. The book value of a firm is computed as the sum of the book value of stockholders' equity (SEQ), deferred taxes (TXDB), and investment tax credit (ITCB) minus the book value of preferred stock (PSTKRV, or PSTKL, or PSTK depending on availability), which are all retrieved from Compustat. BM is the natural logarithm of the ratio of a firm's book value to its market capitalization.

Following Jegadeesh and Titman (1993), intermediate-term momentum (MOM) is a stock's cumulative return over the 11-month period before the portfolio formation month. Short-term reversal (REV) is the excess return generated over the portfolio formation month (Jegadeesh, 1990). Following Ang et al. (2006), I calculate idiosyncratic volatility (IVOL) as the monthly standard deviation of the daily residuals from a regression of daily excess stock returns on the daily excess market returns, small-minus-big size factor, and high-minus-low book-to-market factor. Introduced by Bali et al. (2011), I use the average of five highest maximum daily returns within a month (MAX) as a proxy of the demand for lottery-type stocks. Hou et al. (2015) add return on equity to their q-factor model as a proxy for profitability and annual growth of assets to measure investment. Following their methodology, I quantify the annual growth of total assets (I/A) by the change in the book value of assets (Compustat item AT) divided by lagged AT. To measure quarterly operating profitability (ROE), I divide income before extraordinary items (item IBQ) by one-quarter-lagged book equity.

I generate the liquidity shocks (unexpected liquidity) measure as proposed by Bali et al. (2014) as follows:

$$LIQU_{i,t} = -(ILLIQ_{i,t} - AVGILLIQ_{i|t-12,t-1}), \tag{6}$$

where AVGILLIQ refers to the firm-specific time series average of Amihud's illiquidity measure over the past 12 months. A positive (negative) LIQU indicates an increase (decrease) in firm-specific liquidity relative to its past 12-month average. Following Chordia et al. (2001b), the standard deviation of turnover (SDTURN) is the standard deviation of monthly turnover (TURN) over the past 12 months. Following Akbas et al. (2011), the coefficient of variation in the ILLIQ (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), I estimate each stock's monthly varying liquidity exposure (PS) to innovations in the aggregate liquidity factor. I control for a stock's exposure to the fixed and variable components of Sadka's 2006 liquidity factor. For each stock-month observation, a stock's illiquidity risk loadings on the fixed and the variable components (SADKAF and SADKAV) are obtained using monthly return data over the prior 60 months with a minimum of 24 monthly observations available after controlling for the monthly market returns, and size and book-to-market factors. To capture the systematic component of firm-specific liquidity, Acharya and Pedersen (2005) generate four different beta measures: BETA1 corresponds to the market beta, BETA2 is the covariance between a stock's illiquidity and the market illiquidity, BETA3 estimates the covariance between a stock's return and the market liquidity, and BETA4 is the covariance between a stock's illiquidity and market return. I classify common stocks into 25 test portfolios based on their average daily Amihud (2002) illiquidity measure over the previous year using NYSE breakpoints. Then, I normalize the Amihud illiquidity and estimate market illiquidity and test portfolios' monthly innovations by extracting the residuals from an AR(2) model using a 60-month rolling window with at least 24 monthly observations. Finally, using these illiquidity innovations and returns, I estimate the liquidity betas for the testing portfolios and assign the betas of the illiquidity portfolio to the stocks that compose it. Earnings shocks might result in post-earnings-announcement drift, which might lead to the cross-sectional relation between idiosyncratic liquidity and subsequent stock returns. To control for this effect, I construct a standardized unexpected earnings measure (SUE), defined as changes in earnings from four quarters ago, standardized by its standard deviation over the past eight quarters (Ball and Brown, 1968; Bernard and Thomas, 1989, 1990). Following Bali et al. (2014), I control for volume changes by constructing abnormal dollar volume (VOLDU) in the same way the liquidity shocks measure is constructed. I subtract its past 12-month average from the monthly dollar volume.

As a robustness test, I use the bid–ask spread proxy of Corwin and Schultz (2012) to quantify firm-level monthly-varying (il)liquidity and market-wide (il)liquidity. To compute the bid–ask spread measure, I retrieve firm-specific daily high and low prices from CRSP.[9]

The monthly excess market returns (MKT) and the small-minus-big size (SMB), high-minus-low book-to-market (HML), up-minus-down momentum (UMD), robust-minus-weak profitability (RMW), and conservative-minus-aggressive investment (CMA) factors of Fama and French (1993), Carhart (1997), and Fama and French (2015) are from Kenneth French's data library. In addition, I use the online data library of Kenneth French for the Fama–French 10, 12, and 48 industry classifications. The monthly liquidity factor of Pastor and Stambaugh (2003) is from Lubos Pastor's website. Hou, Xu, and Zhang's (HXZ) empirical q factor model factors (market, size, investment, and profitability) are from Lu Zhang's online data library. Analysts' earnings forecasts are collected from the I/B/E/S dataset and cover the period from 1980 to 2018. The institutional ownership data are from Thompson 13F filings for the 1980–2018 period.

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[8] When constructing market-wide illiquidity, I exclude each stock's own illiquidity. However, each stock's size (weight) is considerably small compared to the size of the stock market. Hence, there is a great correlation between illiquidity beta and illiquidity beta multiplied by absolute value of the market-wide illiquidity ($\varphi = 0.99$).

[9] See Corwin and Schultz (2012) for a detailed computation of effective bid–ask spread.

Table 3
Univariate sorts on illiquidity.

| | Contemporaneous | | | | | | One-month-ahead | | | | | |
| | EW | | | VW | | | EW | | | VW | | |
	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q
Low ILLIQ	1.07	0.58	0.58	1.11	0.63	0.64	0.57	0.07	0.07	0.48	0.01	0.01
	(5.01)	(11.04)	(10.70)	(5.96)	(12.94)	(11.00)	(2.60)	(1.85)	(2.01)	(2.57)	(1.58)	(0.88)
2	1.30	0.75	0.76	1.49	0.93	0.96	0.68	0.13	0.16	0.59	0.03	0.04
	(4.88)	(12.52)	(10.32)	(6.14)	(11.69)	(11.43)	(2.65)	(2.46)	(2.22)	(2.57)	(0.74)	(0.83)
3	0.94	0.42	0.46	1.37	0.82	0.86	0.59	0.07	0.12	0.50	−0.05	−0.03
	(3.12)	(4.49)	(3.30)	(5.15)	(8.24)	(6.62)	(2.02)	(0.85)	(0.94)	(1.96)	(−1.03)	(−0.32)
4	0.51	0.02	0.11	1.20	0.65	0.74	0.60	0.09	0.18	0.49	−0.10	−0.04
	(1.63)	(0.15)	(0.59)	(4.25)	(4.95)	(4.27)	(1.93)	(0.75)	(1.05)	(1.83)	(−1.34)	(−0.41)
High ILLIQ	−0.46	−0.85	−0.68	0.81	0.34	0.49	0.92	0.52	0.67	0.17	−0.32	−0.21
	(−1.38)	(−4.67)	(−2.98)	(2.73)	(2.28)	(2.54)	(2.66)	(2.76)	(2.98)	(0.60)	(−2.62)	(−1.41)
High-Low	−1.54	−1.44	−1.27	−0.29	−0.29	−0.14	0.34	0.45	0.60	−0.31	−0.34	−0.22
difference	(−7.66)	(−7.24)	(−5.02)	(−1.47)	(−1.89)	(−0.64)	(1.78)	(2.31)	(2.61)	(−1.72)	(−2.67)	(−1.41)

Quintile portfolios are constructed every month by sorting all stocks in the CRSP universe based on their Amihud (2002) illiquidity measure (ILLIQ). Quintile portfolio 1 (5) consists of stocks with the lowest (highest) illiquidity. The table presents average equal-weighted (EW) and value-weighted (VW) excess returns (RET-RF) and alphas (α_7 and α_Q). First (last) six columns document contemporaneous (one-month-ahead) returns. The last rows present the average monthly return and alpha differences between quintile portfolios 5 (High) and 1 (Low). Newey and West (1987) adjusted *t-statistics* using six lags are reported in parentheses. The sample period is from January 1969 to December 2018.

3. Empirical results

I conduct parametric and nonparametric tests to estimate the predictive power of Amihud's 2002 illiquidity measure and the illiquidity components over stock returns. To test the predictive power of firm-specific monthly-varying illiquidity measures, I quantify the illiquidity components. These illiquidity components are estimated through monthly rolling regressions of individual stocks' illiquidity on market-wide illiquidity measure using a 60-month fixed window estimation (Eq. (4)). The illiquidity alpha is the intercept term that can be interpreted as expected illiquidity. Systematic illiquidity is the portion of the illiquidity explained by market-wide illiquidity, whereas idiosyncratic illiquidity is equal to the residual term. The first set of illiquidity measures is estimated using the sample from January 1964 to December 1968. Then, stock-specific illiquidity components are used to predict one-month-ahead excess stock returns (January 1969). This rolling window regression approach is conducted until the final month of the sample (December 2018). The cross-sectional stock return predictability results span the period from January 1969 to December 2018.

As a benchmark, Section 3.1 reports the well-documented illiquidity premium. In Section 3.2, I investigate the firm-level cross-sectional relationship between the illiquidity alpha and systematic illiquidity and stock returns. The rest of the empirical results are based on the cross-sectional relationship between idiosyncratic (il)liquidity and subsequent stock returns. More specifically, first, I discuss average stock characteristics to obtain a clear picture of the composition of the idiosyncratic liquidity portfolios. Second, I conduct univariate portfolio-level analyses. Third, I employ firm-level cross-sectional Fama and MacBeth (1973) regressions to test the predictive power of idiosyncratic liquidity on stock returns while controlling for various firm-level characteristics and liquidity factors. Fourth, portfolio sorts and cross-sectional regressions document that idiosyncratic liquidity predicts future stock returns up to four months. Finally, I provide evidence from robustness checks.

3.1. Illiquidity premium

This subsection, as a benchmark, documents the cross-sectional relationship between Amihud (2002) illiquidity and stock returns. More specifically, Table 3 reports contemporaneous (first six columns) and one-month-ahead (last six columns) excess returns and alphas generated by the illiquidity sorted quintile portfolios. α_7 is the risk-adjusted return relative to the Fama–French-5 factors, Carhart's 1997 momentum factor, and Pastor and Stambaugh's 2003 liquidity factor, while α_Q is the alpha relative to HXZ (2015) q-factor model in which the risk factors are excess market return, market capitalization, investment, and profitability.

Consistent with Amihud (2002), Columns (1) to (3) of Table 3 suggest a negative and significant cross-sectional relationship between illiquidity and the contemporaneous stock returns. More specifically, the excess return spread between the extreme equal-weighted illiquidity portfolios is −1.54% per month with a Newey and West (1987) adjusted *t-statistic* of −7.66. In addition, common risk factor models fail to explain the significant return difference between the high and low illiquidity portfolios. A zero-cost high-low equal-weighted illiquidity strategy generates −1.44% (−1.27%) contemporaneous α_7 (α_Q) per month with a *t-statistic* of −7.24 (−5.02). The results suggest that high levels of illiquidity (low levels of liquidity) result in decreases in stock prices.[10]

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[10] The contemporaneous value-weighted α_7 difference between extreme illiquidity portfolios is −0.29% per month with a *t-statistic* of −1.89, whereas the α_Q spread is negative albeit insignificant.

Table 4
Univariate sorts on illiquidity components.

	Panel A: Uniform sorts on illiquidity beta						Panel B: Uniform sorts on systematic illiquidity					
	EW			VW			EW			VW		
	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q
Port 1	0.66	0.10	0.10	0.43	−0.07	−0.08	0.63	0.02	0.01	0.50	−0.01	−0.01
	(3.15)	(1.48)	(1.33)	(2.30)	(−1.35)	(−1.67)	(3.22)	(0.53)	(0.22)	(2.81)	(−0.07)	(−0.37)
2	0.69	0.03	0.03	0.58	−0.01	0.01	0.69	0.04	0.04	0.58	−0.02	−0.03
	(3.20)	(0.63)	(0.42)	(2.85)	(−0.04)	(0.08)	(3.09)	(0.94)	(0.54)	(2.65)	(−0.48)	(−0.64)
3	0.84	0.19	0.22	0.71	0.02	0.06	0.84	0.19	0.23	0.73	0.03	0.08
	(3.35)	(2.90)	(2.19)	(2.95)	(0.41)	(1.06)	(3.26)	(3.13)	(2.51)	(2.90)	(0.71)	(1.49)
4	0.87	0.21	0.27	0.69	0.01	0.06	0.83	0.20	0.26	0.63	−0.06	−0.01
	(3.03)	(2.29)	(2.30)	(2.58)	(0.22)	(0.96)	(2.88)	(1.88)	(1.99)	(2.33)	(−0.92)	(−0.02)
Port 5	1.09	0.50	0.64	0.58	−0.09	−0.00	1.14	0.58	0.72	0.55	−0.06	0.04
	(3.21)	(3.09)	(3.40)	(1.92)	(−0.84)	(−0.01)	(3.41)	(3.58)	(3.81)	(1.86)	(−0.55)	(0.40)
5–1	0.43	0.40	0.53	0.15	−0.02	0.08	0.51	0.56	0.70	0.05	−0.06	0.05
difference	(2.41)	(2.57)	(3.20)	(0.83)	(−0.21)	(0.71)	(2.48)	(3.24)	(3.76)	(0.27)	(−0.53)	(0.44)

	Panel C: Uniform sorts on illiquidity alpha					
	EW			VW		
	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q
Port 1	0.75	0.09	0.11	0.59	−0.11	−0.09
	(2.77)	(1.08)	(1.09)	(2.20)	(−1.42)	(−1.03)
2	0.69	−0.01	−0.05	0.51	−0.12	−0.14
	(3.12)	(−0.33)	(−0.84)	(2.38)	(−1.82)	(−1.92)
3	0.70	0.13	0.14	0.57	0.06	0.07
	(3.31)	(1.96)	(1.38)	(2.93)	(1.13)	(1.24)
4	0.92	0.33	0.42	0.66	0.12	0.20
	(3.39)	(3.45)	(3.16)	(2.69)	(1.45)	(2.26)
Port 5	1.08	0.51	0.66	0.56	−0.03	0.11
	(3.23)	(3.08)	(3.44)	(2.00)	(−0.31)	(1.03)
5–1	0.33	0.41	0.55	−0.02	0.08	0.21
difference	(2.46)	(3.05)	(3.94)	(−0.17)	(0.63)	(1.33)

Quintile portfolios are constructed every month by sorting stocks based on their illiquidity components during the previous month. The table presents average excess returns (RET-RF) and alphas (α_7 and α_Q). Panel A reports returns generated by illiquidity beta sorted portfolios. Panel B (C) documents returns of systematic illiquidity (illiquidity alpha) sorted quintiles. The last rows present the return differences between quintile portfolios 5 and 1. Newey and West (1987) adjusted *t-statistics* using six lags are reported in parentheses.

Columns (7) to (9) document the one-month-ahead equal-weighted excess returns and the alphas generated by illiquidity sorted portfolios. Stocks in the highest illiquidity quintile generate 0.34% more monthly return than stocks in the lowest illiquidity quintile portfolio. In addition, the risk-adjusted return difference between the extreme illiquidity quintiles is positive and significant ($\alpha_7 = 0.45\%$ per month with a *t-statistic* of 2.35; $\alpha_Q = 0.60\%$ per month with a *t-statistic* of 2.61). Equal-weighted portfolio results document a positive and significant relationship between illiquidity and one-month-ahead stock returns.[11]

These results are consistent with the hypothesis that illiquidity is priced: a low liquidity (high illiquidity) decreases the contemporaneous stock prices and increases future risk premium. As a result, illiquid stocks generate high returns.[12]

3.2. Illiquidity components

In this subsection, I investigate the importance of illiquidity beta, systematic illiquidity, and illiquidity alpha in the cross-sectional pricing of individual stocks. Table 4 reports one-month-ahead excess returns and alphas generated by each illiquidity component sorted quintile portfolios. Panel A reports returns generated by illiquidity beta sorted quintile portfolios. Panel B (C) documents the univariate equal-weighted (EW) and value-weighted (VW) average excess monthly returns and alphas generated by systematic illiquidity (illiquidity alpha) sorted portfolios. The results suggest a positive but weak cross-sectional relationship between the illiquidity components and the one-month-ahead stock returns.

More specifically, the highest (quintile 5) equal-weighted illiquidity beta portfolio produces 1.09% one-month-ahead excess return, whereas the lowest (quintile 1) equal-weighted portfolio generates 0.66% one-month-ahead excess return per month. The equal-weighted return spread between the extreme illiquidity beta portfolios is 0.43% per month with a Newey and West (1987)

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[11] Consistently, firm-level cross-sectional regressions document a negative (positive) relationship between stock-level illiquidity and contemporaneous (one-month-ahead) excess stock returns.

[12] The value-weighted raw return spread between the extreme illiquidity portfolios is −0.31% per month with a *t-statistic* of −1.72. The results suggest that illiquidity premium disappears when larger stocks have larger weights in the portfolios (value-weighted portfolios). The results are consistent with Cakici and Zaremba (2021) who document that the illiquidity premium exists only among microcap stocks. Outside the microcap universe, they find no liquidity effect.

adjusted *t-statistic* of 2.41. More importantly, the alpha spread between the highest and the lowest illiquidity beta quintiles is positive and significant: 0.40% α_7 (*t-statistic* = 2.57) and 0.53% α_Q (*t-statistic* = 3.20) per month. However, when moving to the value-weighted portfolios, the return spread between the extreme illiquidity beta quintiles is positive but insignificant (0.15% per month with a *t-statistic* of 0.83). Similarly, the value-weighted alpha spreads between quintile 5 and quintile 1 are insignificant. This means that if market-wide illiquidity (liquidity) increases (decreases) as a whole, investors might encounter severe difficulty in selling highly sensitive stocks to market-wide illiquidity. Hence, risk-averse investors demand extra compensation in the form of higher expected return to hold stocks whose liquidity is highly sensitive to market-wide illiquidity (stocks with high illiquidity beta). However, this relationship disappears when larger stocks have larger weights in the portfolios.

Similarly, the equal-weighted return and alpha spreads between the extreme systematic illiquidity portfolios are positive and significant.[13] Stocks in the highest SYS-ILLIQ portfolio generate 0.51% higher monthly equal-weighted return compared to stocks in the lowest SYS-ILLIQ quintile. The α_7 (α_Q) spread between the highest and the lowest SYS-ILLIQ portfolios is 0.56% (0.70%) per month with a *t-statistic* of 3.24 (3.76). The last three columns report value-weighted returns generated by SYS-ILLIQ sorted quintile portfolios. While the highest (lowest) SYS-ILLIQ portfolio produces 0.55% (0.50%) one-month-ahead excess return, the return and alpha spreads between them are insignificant.[14]

Panel C reports returns generated by illiquidity alpha sorted quintiles. α_{ILLIQ} is the intercept term from Eq. (4) and can be considered as expected illiquidity. While the equal-weighted return and alpha spreads between the extreme α_{ILLIQ} quintiles are positive and significant [RET-RF = 0.33% (*t-statistic* = 2.46), α_7 = 0.41% (*t-statistic* = 3.05), α_Q = 0.55% (*t-statistic* = 3.94) per month], the value-weighted differences are insignificant [RET-RF = −0.02% (*t-statistic* = −0.17), α_7 = 0.08% (*t-statistic* = 0.63), α_Q = 0.21% (*t-statistic* = 1.33) per month]. The equal-weighted portfolio sorts suggest a positive relationship between illiquidity beta, systematic illiquidity, illiquidity alpha and subsequent stock returns. However, the relationship disappears when stocks have weights proportional to their market capitalization. In addition, when stocks with a price less than $5 are excluded, the return and alpha spreads between the extreme illiquidity components portfolios are insignificant.

In addition, I test the cross-sectional predictive power of the illiquidity components through firm-level cross-sectional Fama and MacBeth (1973) regressions. Firm-level cross-sectional regressions have two significant advantages over portfolio sorts. First, portfolio sorts hide a significant amount of information in the cross-section due to the accumulation of stocks into portfolios. Second, cross-sectional regressions give the advantage of controlling for several simultaneous effects and factors.

Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} * ILLIQ_{i,t} * + \lambda_{2,t} * X_{i,t} + \epsilon_{i,t+1}, \tag{7}$$

where $R_{i,t+1}$ is the realized excess return generated by stock *i* in month *t+1*, ILLIQ is a illiquidity component (systematic illiquidity, illiquidity beta, illiquidity alpha) estimated through Eq. (4). $X_{i,t}$ is a collection of firm-level control variables, such as market beta (BETA), size (SIZE), book-to-market (BM), short-term reversal (REV), intermediate-term momentum (MOM), idiosyncratic volatility (IVOL), average of maximum daily returns (MAX), asset growth (I/A), and return on equity (ROE). Cross-sectional regressions are run for each month. Then, time series averages of the estimated slope coefficients are calculated. The sample period is from January 1969 to December 2018. Table 5 reports the time-series averages of the slope coefficients from the regressions of one-month-ahead excess stock returns on illiquidity components and the control variables. Columns (1) to (6) give the results of univariate cross-sectional regressions of stock returns on illiquidity measures. Columns (7) to (9) report the results of multivariate regressions of excess stock returns on illiquidity measures and control variables for the sample of stocks with a price of $5 or more.

The univariate regression results reported in the columns (1) to (3) (where all stocks in the CRSP universe are included) indicate a positive and statistically significant relation between illiquidity alpha, systematic illiquidity, and the cross-section of future stock returns. The average slope from the monthly regressions of realized returns on α_{ILLIQ} (SYS-ILLIQ) alone is 0.366 (0.149) with a Newey–West *t-statistic* of 3.44 (1.81). Columns (4) to (9) report regression results where stocks with a price less than $5 are excluded. These results suggest that the illiquidity components are positively priced only when small stocks are included in the regressions.

Equal-weighted portfolio sorts and firm-level cross-sectional regressions suggest a positive relationship between systematic illiquidity and the cross-section of stock returns. If the market-wide illiquidity (liquidity) increases (decreases) as a whole, investors might encounter difficulty in selling their stocks with high exposure to the market-wide illiquidity. Hence, risk-averse investors demand extra compensation in the form of higher expected return to hold stocks whose illiquidity has high covariance with market-wide illiquidity (stocks with high systematic illiquidity). However, this relationship disappears when larger stocks have larger weights in the portfolio sorts (value-weighted portfolios) and when small stocks are excluded. Similarly, investors demand a premium to hold stocks with high illiquidity alpha. However, the alpha premium also disappears within value-weighted portfolio sorts and stock-level cross-sectional regressions excluding very small stocks.

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[13] Systematic illiquidity is equal to stock-level illiquidity beta multiplied by detrended market-wide illiquidity (where I detrend by subtracting four-month moving average). This implies that even a very small decrease or increase (from positive to negative or from negative to positive) in the detrended market-wide illiquidity measure would change the portfolios that each stock belongs to from month to month. In order to avoid such disruptions, I take the absolute value of systematic illiquidity and create quintile portfolios accordingly.

[14] Table A.1 in the Online Appendix reports the equal-weighted and value-weighted excess returns and alphas generated by double-sorted portfolios where all stocks in the CRSP universe are included. Panel A (B) reports returns earned by idiosyncratic liquidity controlled systematic illiquidity sorted (systematic illiquidity controlled idiosyncratic liquidity sorted) quintile portfolios. Columns (1) to (3) of Panel A shows that the high-low SYS-ILLIQ strategy continues to generate positive and significant equal-weighted excess and risk-adjusted returns when portfolios are neutralized to idiosyncratic liquidity. However, consistent with Table 4, the relationship disappears once larger stocks have larger weights in the portfolios (value-weighted).

Table 5
Firm-level cross-sectional Fama–MacBeth regressions on illiquidity components.

	CRSP universe			< **\$5 are excluded**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α_{ILLIQ}	0.366			−0.046			0.039		
	(3.44)			(−0.71)			(0.50)		
β^{ILLIQ}		0.011			−0.004			−0.012	
		(0.82)			(−0.48)			(−1.39)	
SYS-ILLIQ			0.149			0.539			0.252
			(1.81)			(1.30)			(0.70)
BETA							0.014	0.015	0.015
							(1.44)	(1.53)	(1.51)
SIZE							−0.059	−0.065	−0.066
							(−2.08)	(−2.32)	(−2.36)
BM							0.212	0.212	0.212
							(3.72)	(3.73)	(3.72)
REV							−0.035	−0.035	−0.035
							(−6.46)	(−6.54)	(−6.35)
MOM							0.006	0.006	0.006
							(4.12)	(4.20)	(4.22)
IVOL							−0.036	−0.031	−0.029
							(−0.55)	(−0.48)	(−0.45)
MAX							−0.115	−0.117	−0.118
							(−2.17)	(−2.19)	(−2.20)
I/A							−0.257	−0.258	−0.257
							(−3.85)	(−3.74)	(−3.73)
ROE							0.144	0.144	0.145
							(10.82)	(10.79)	(10.85)
Intercept	0.008	0.008	0.008	0.007	0.007	0.007	0.013	0.014	0.014
	(3.35)	(3.37)	(3.34)	(3.28)	(3.34)	(3.35)	(3.29)	(3.47)	(3.51)
Avg. R^2	0.003	0.006	0.006	0.001	0.004	0.004	0.081	0.081	0.081

This table reports the time-series averages of the slope coefficients obtained from univariate and multivariate regressions of one-month-ahead excess stock returns on illiquidity alpha, illiquidity beta, systematic illiquidity, and a set of lagged firm-level characteristics and risk factors using the firm-level cross-sectional Fama and MacBeth (1973) methodology. Columns (1) to (6) report univariate regression results and columns (7) to (9) document the slope coefficients obtained from multivariate regressions of stock returns on illiquidity measures and firm-specific control variables. Newey and West (1987) adjusted *t-statistics* using six lags are reported in parentheses. The sample period is from January 1969 to December 2018.

3.3. Idiosyncratic (il)liquidity

After documenting the positive, albeit weak relation between systematic illiquidity, illiquidity alpha, and one-month-ahead stock returns, I focus on the cross-sectional pricing of idiosyncratic (il)liquidity. Idiosyncratic illiquidity is the firm-level monthly-varying illiquidity minus the systematic illiquidity component and the intercept term computed using a 60-month fixed window estimation (Eq. (4)). Idiosyncratic liquidity is equal to the negative sign of idiosyncratic illiquidity.

3.3.1. Summary statistics

Upcoming subsections report a significantly positive relationship between IDIO-LIQ and contemporaneous and subsequent stock returns. Before discussing the cross-sectional relationship between IDIO-LIQ and stock returns, I examine the average characteristics of stocks with low versus high idiosyncratic liquidity using the firm-level cross-sectional Fama and MacBeth (1973) regression methodology.

Table 6 presents the time-series averages of the slope coefficients obtained from the univariate and multivariate regressions of idiosyncratic liquidity (IDIO-LIQ) on the stock-level characteristics and risk factors. Idiosyncratic liquidity is equal to the negative sign of idiosyncratic illiquidity. As expected, according to column (1) of Table 6, there is a negative (positive) and significant relationship between Amihud's illiquidity (liquidity) measure and IDIO-LIQ. In other words, stocks with high idiosyncratic liquidity tend to be liquid. Column (13) reports the multivariate regression results of IDIO-LIQ on all control variables. The average slope coefficient on market beta is negative and significant, implying that high IDIO-LIQ stocks (and high returns/alpha) have a low market beta. This result is consistent with Frazzini and Pedersen (2014), providing evidence that stocks with higher market beta earn lower one-month-ahead returns and alpha. Column (13) shows that the average slope coefficients on SIZE and BM are significantly negative and positive, respectively. This implies that stocks with high IDIO-LIQ (and high returns/alpha) are small and value stocks, consistent with Fama and French (1992, 1993) findings that small/value stocks produce higher one-month-ahead returns and alpha than big/growth stocks.

Column (5) reports a significantly positive relationship between IDIO-LIQ and (contemporaneous) excess return generated during the portfolio formation month (REV). Columns (6) and (13) document a positive and significant cross-sectional relationship between IDIO-LIQ and intermediate-term-momentum. To explore the positive association, I investigate the persistence behaviour of IDIO-LIQ using a month-to-month portfolio transition matrix, which shows the average probability that a stock in quintile "*i*" will be in

Table 6
Average stock characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
ILLIQ	−0.310												−0.378
	(−12.69)												(−15.93)
BETA		−0.036											−0.576
		(−0.76)											(−5.02)
SIZE			−0.060										−0.241
			(−3.25)										(−8.01)
BM				−0.064									0.320
				(−2.01)									(5.10)
REV					2.929								0.310
					(3.25)								(0.37)
MOM						0.553							0.713
						(2.21)							(2.00)
IVOL							0.044						0.331
							(0.48)						(1.87)
MAX								0.068					0.179
								(1.01)					(1.75)
I/A									−0.055				−0.123
									(−1.28)				(−3.48)
ROE										0.459			1.990
										(1.39)			(2.53)
INST											−0.480		
											(−2.37)		
CVRG												−0.009	
												(−2.01)	
Intercept	0.493	0.113	0.851	0.033	0.045	0.023	0.025	−0.060	0.065	0.052	0.248	0.047	3.381
	(9.85)	(1.67)	(3.07)	(0.96)	(1.87)	(0.81)	(0.18)	(−0.34)	(2.96)	(2.55)	(1.73)	(1.77)	(6.35)
Avg. R^2	0.214	0.003	0.010	0.004	0.012	0.009	0.017	0.017	0.005	0.003	0.004	0.002	0.278

This table reports the time series averages of the slope coefficients obtained from the univariate and multivariate regressions of idiosyncratic liquidity measure on Amihud (2002) illiquidity, and a set of firm-level characteristics and risk factors, such as market beta, size, book-to-market ratio, excess return during the portfolio formation month, intermediate-term-momentum, idiosyncratic volatility, maximum daily return during the portfolio formation month, asset growth (I/A), return on equity (ROE), institutional holdings (INST), and analyst coverage (CVRG) using the firm-level cross-sectional Fama and MacBeth (1973) methodology. Columns (1) to (12) report univariate regression results, whereas column (13) documents the slope coefficients obtained from the multivariate regression of idiosyncratic liquidity on firm-specific characteristics. Newey and West (1987) adjusted *t-statistics* using six lags are reported in parentheses.

quintile *"j"* next month. If the idiosyncratic liquidity components are entirely random, then all the probabilities should be around 20%. On the contrary, there is clear evidence that IDIO-LIQ is persistent across time periods, with all diagonal elements of the transition matrix exceeding 20%. As a result, if a stock appears in the highest (lowest) IDIO-LIQ quintile in the portfolio formation month, there is a high probability that it will appear in the same quintile portfolio in the upcoming months and produce positively (negatively) significant returns. Hence, there is a positive association between IDIO-LIQ and intermediate-term momentum. Column (13) documents that high IDIO-LIQ stocks tend to generate high contemporaneous idiosyncratic volatility and maximum daily returns, suggesting that high IDIO-LIQ stocks tend to be lottery-like stocks that are likely to be held by retail investors. Column (13) shows that the average slopes on I/A and ROE are negative and positive respectively, indicating that stocks with low idiosyncratic liquidity (and high returns/alpha) have high asset growth and low return on equity. This result is consistent with Fama and French (2015) and Hou et al. (2015). Columns (11) and (12) report univariate regression results of idiosyncratic liquidity on institutional holdings and analyst coverage. The results point to a negative relationship between IDIO-LIQ and institutional holdings and analyst coverage. This means that stocks with high idiosyncratic liquidity tend to attract less investor attention (low analyst coverage and low institutional holdings), which are more prone to mispricing.[15]

3.3.2. Univariate portfolio-level analyses

In this subsection, I discuss univariate portfolio-level analyses, where quintile portfolios are constructed every month by sorting stocks based on their idiosyncratic liquidity (IDIO-LIQ). Table 7 documents the time-series averages of contemporaneous and one-month-ahead value-weighted excess returns and alphas generated by IDIO-LIQ sorted value-weighted quintile portfolios.[16] Panel A reports the returns for the CRSP universe. The sample in Panel B does not include stocks with a price less than $5. Columns (1) to (3) ((4) to (6)) present contemporaneous (one-month-ahead) excess returns and alphas. The last rows present excess returns and risk-adjusted returns generated by a zero-cost IDIO-LIQ strategy.

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[15] Institutional ownership and analyst coverage data are available since 1980. Due to shorter data availability, I do not include these two variables in the multivariate regression specification.

[16] Subsequent tables report value-weighted returns. It is important to note that equal-weighted portfolios generate similar results within all value-weighted portfolio analyses, which generate significant return and alpha spreads.

Table 7
Univariate portfolios of stocks sorted by idiosyncratic liquidity.

	Panel A: CRSP universe					
	Contemporaneous			One-month-ahead		
	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q
Low IDIO-LIQ	0.37	−0.28	−0.14	0.35	−0.27	−0.22
	(1.40)	(−2.18)	(−1.07)	(1.33)	(−3.44)	(−2.47)
2	0.30	−0.33	−0.31	0.48	−0.10	−0.11
	(1.30)	(−3.37)	(−2.81)	(2.08)	(−1.56)	(−1.79)
3	0.92	0.38	0.38	0.49	−0.09	−0.08
	(4.53)	(5.47)	(5.91)	(2.55)	(−2.40)	(−2.13)
4	2.63	2.05	2..06	0.73	0.13	0.16
	(11.01)	(13.81)	(14.77)	(3.61)	(2.16)	(2.41)
High IDIO-LIQ	4.29	3.67	3.71	0.97	0.28	0.38
	(13.78)	(20.26)	(19.92)	(3.84)	(3.32)	(4.38)
High-Low	3.92	3.95	3.86	0.62	0.55	0.60
difference	(21.70)	(18.68)	(17.79)	(6.05)	(5.09)	(5.40)
	Panel B: < \$5 are excluded					
	Contemporaneous			One-month-ahead		
	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q
Low IDIO-LIQ	0.63	−0.09	−0.03	0.44	−0.22	−0.21
	(2.55)	(−0.78)	(−0.28)	(1.80)	(−3.73)	(−2.87)
2	0.48	−0.12	−0.08	0.45	−0.17	−0.18
	(2.07)	(−1.17)	(−0.70)	(2.05)	(−2.91)	(−3.30)
3	0.92	0.36	0.37	0.51	−0.03	−0.04
	(4.58)	(5.56)	(5.81)	(2.61)	(0.80)	(−1.11)
4	2.37	1.76	1.76	0.69	0.06	0.07
	(11.04)	(15.17)	(16.42)	(3.36)	(1.16)	(1.32)
High IDIO-LIQ	3.94	3.29	3.31	0.85	0.20	0.23
	(14.11)	(21.63)	(22.53)	(3.79)	(2.73)	(2.78)
High-Low	3.30	3.38	3.34	0.41	0.42	0.44
difference	(19.96)	(19.26)	(19.76)	(3.76)	(4.71)	(5.08)

Quintile portfolios are constructed every month by sorting stocks based on their idiosyncratic liquidity. Quintile portfolio 1 (5) consists of stocks with the lowest (highest) idiosyncratic liquidity. The table presents average excess returns (RET-RF) and alphas. First (last) three columns document contemporaneous (one-month-ahead) returns. While Panel A reports the returns for the CRSP universe, Panel B excludes stocks with a price less than \$5. The last rows present the average monthly return and alpha differences between quintile portfolios 5 (High) and 1 (Low). Newey and West (1987) adjusted *t-statistics* using six lags are reported in parentheses. The sample period is from January 1969 to December 2018.

Table 7 reports a positive relationship between IDIO-LIQ and the contemporaneous returns. The time-series average of excess return for stocks within the highest idiosyncratic liquidity quintile is 3.92%. Stocks in the lowest IDIO-LIQ quintile produce an average return of 0.37%. The value-weighted return difference between the extreme IDIO-LIQ quintile portfolios is 3.92% with a Newey–West adjusted *t-statistic* of 21.70. Moreover, the return spread between the extreme quintiles cannot be explained by common risk factors (α_7 = 3.95% per month; α_Q = 3.86% per month). The results are consistent with the positive illiquidity premium according to which risk-averse investors demand a premium to hold illiquid stocks and therefore leads to a sudden decrease in the stock price.

Columns (4) to (6) of Table 7 report one-month-ahead returns on portfolios that are formed by sorting on IDIO-LIQ. From quintile portfolio 1 to 5, excess returns and alphas exhibit monotonicity. Stocks in the lowest IDIO-LIQ quintile have a monthly value-weighted excess return of 35 bps. Then, excess returns tend to increase monotonically. The time-series average of excess returns generated by stocks in the highest IDIO-LIQ quintile is 97 bps per month. The average return difference between the extreme IDIO-LIQ quintiles is 0.62% per month with a Newey and West (1987) adjusted *t-statistic* of 6.05, indicating that equities with higher IDIO-LIQ generate significantly higher excess returns.[17]

Next, I examine whether standard asset pricing models can explain the excess return differences between the extreme IDIO-LIQ quintiles. To test this, I compute the alphas (risk-adjusted returns) generated by IDIO-LIQ sorted quintile portfolios. Portfolio 1 has a value-weighted α_7 (α_Q) of −27 (−22) bps, whereas portfolio 5 generates 28 (38) bps α_7 (α_Q). The α_7 (α_Q) generated by a zero-cost high-low IDIO-LIQ strategy is equal to 55 (60) bps per month with a *t-statistic* of 5.09 (5.40), which is both economically and statistically significant. An important question is the source of the economically and statistically significant risk-adjusted return spread between the extreme IDIO-LIQ quintile portfolios. To answer this, I investigate the economic and statistical significance of

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[17] Panel B of Table A.1 in the Online Appendix reports one-month-ahead excess returns and alphas generated systematic illiquidity controlled idiosyncratic liquidity sorted quintile portfolios. The results show that the positive cross-sectional relationship between idiosyncratic liquidity and one-month-ahead stock returns is robust to controls to systematic illiquidity.

the alphas earned by the lowest and the highest IDIO-LIQ portfolios. As documented, the highest (lowest) IDIO-LIQ quintile portfolio generates a positively (negatively) significant alpha. Therefore, both outperformance by high IDIO-LIQ stocks and underperformance by low IDIO-LIQ stocks generate a positively significant risk-adjusted returns difference between the extreme IDIO-LIQ quintile portfolios.

Panel B reports contemporaneous and one-month-ahead returns for the sample that does not include stocks with a price less than $5.[18] IDIO-LIQ continues to be positively priced in the cross-section of stock returns. The contemporaneous return spread between the extreme IDIO-LIQ quintile portfolios is 3.30% per month with a *t-statistic* of 19.96. In addition, the risk-adjusted return spreads between quintile 5 and quintile 1 are positive and significant. The one-month-ahead return spread between the highest and the lowest IDIO-LIQ portfolios is 0.41% per month with a *t-statistic* of 3.76. Moreover, a zero-cost high-low IDIO-LIQ strategy produces 42 (44) bps α_7 (α_Q) with a *t-statistic* of 4.71 (5.08). The results in Table 7 indicate that idiosyncratic liquidity is positively associated with contemporaneous and one-month-ahead stock returns. These findings point an at least one-month underreaction to idiosyncratic liquidity.

3.3.3. Firm-level cross-sectional regression analysis

In addition to portfolio-level analyses, in this subsection, I examine the cross-sectional pricing of IDIO-LIQ on contemporaneous and one-month-ahead stock returns while controlling for various return predictors, such as firm-specific characteristics and (il)liquidity measures. I run firm-level cross-sectional Fama and MacBeth (1973) regressions of the form:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} * IDIO - LIQ_{i,t} * + \lambda_{2,t} * X_{i,t} + \epsilon_{i,t+1}, \tag{8}$$

where $R_{i,t+1}$ is the realized excess return generated by stock i in month $t+1$ (for contemporaneous regressions: $R_{i,t}$), IDIO-LIQ is the negative sign of the idiosyncratic illiquidity component estimated through Eq. (4). $X_{i,t}$ is a collection of firm-level control variables and risk factors.

Table 8 presents the time series averages of the slope coefficients from the regressions of excess stock returns on idiosyncratic liquidity (IDIO-LIQ) and their associated Newey and West (1987) adjusted t-statistics. Columns (1) to (3) present contemporaneous regression results, whereas the dependent variable in columns (4) to (6) is the one-month-ahead excess stock return.

Columns (1) and (4) report univariate regression results. Columns (2) and (5) give the results of the baseline model in which the control variables are the market beta (BETA), natural logarithms of market capitalization (SIZE), and book-to-market ratio (BM).[19] I next add common return predictors, including short-term reversal (REV), momentum (MOM), idiosyncratic volatility (IVOL), the average of five highest maximum daily returns within the portfolio formation month (MAX), annual growth of total assets (I/A), operating profitability (ROE), and liquidity-based measures, such as the liquidity shocks measure (LIQU) of Bali et al. (2014), the coefficient of variance in the Amihud's illiquidity (CVILLIQ), the standard deviation of turnover (SDTURN), Pastor and Stambaugh's liquidity beta (PS), Acharya and Pedersen's liquidity betas (BETA1, BETA2, BETA3, BETA4), exposures to the fixed and variable components of Sadka's liquidity factor (SADKAF and SADKAV), standardized unexpected earnings (SUE), and abnormal dollar trading volume (VOLDU) to the regressions for columns (3) and (6).

Column (1) gives the univariate regression result in which IDIO-LIQ has a significantly positive coefficient of 0.366 with a *t-statistic* of 8.72. To determine the economic significance, I use time-series averages of the median values of IDIO-LIQ in the extreme quintile portfolios. The time-series average of IDIO-LIQ in the lowest (highest) IDIO-LIQ quintile is −1.54 (1.99). The time-series average difference between the lowest and highest IDIO-LIQ quintile is 3.53[= 1.99−(−1.54)]. If a stock were to move from the first to the fifth IDIO-LIQ quintile, its contemporaneous return increases by 1.29% per month [3.53*0.366]. Similarly, column (4) reports the univariate regression result where IDIO-LIQ has significant predictive power on one-month-ahead stock returns with a positive coefficient of 0.117 with a t-statistic of 2.83. Similarly, if a stock moves from the first to the fifth IDIO-LIQ quintile, its expected return increases by 0.41% per month. Consistent with the portfolio-level analyses, the univariate regression results suggest positive cross-sectional pricing of IDIO-LIQ in both contemporaneous and one-month-ahead stock returns.

In general, the coefficients on the control variables are consistent with prior empirical studies. Consistent with Fama and French (1992, 1993), column (6) documents a negative and significant relationship between size and stock returns, and value stocks are riskier and earn higher future returns. Intermediate-term momentum positively predicts one-month-ahead stock returns (Jegadeesh and Titman, 1993), whereas short-term reversal is negatively priced (Jegadeesh, 1990). There is a negative and significant relationship between the proxy for demand for lottery-type stocks and subsequent returns (Bali et al., 2011). Asset growth is negatively priced, whereas return on equity is positively priced. The variation in illiquidity is positive and significant at the 10% level of significance. There is a positive and significant relationship between the stock-level liquidity shocks measure of Bali et al. (2014) and subsequent stock returns. As Chordia et al. (2001a) and Pereira and Zhang (2010) document, there is a negative and significant relationship between the standard deviation of turnover and one-month-ahead stock returns. The coefficient on the exposure to the systematic liquidity risk (PS) is positive, albeit insignificant. While the four betas proposed by Acharya and Pedersen (2005) and Sadka's 2006 fixed liquidity beta fail to explain the cross-section of stock returns significantly, Sadka's 2006 variable liquidity beta is negatively priced. Both unexpected earnings (SUE) and abnormal trading volume (VOLDU) are positively priced in the cross-section of stock returns.

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[18] In the rest of the analyses, I exclude stocks with a price less than $5.

[19] This regression specification can be interpreted as a modification of the Fama–French 3 factor model which adds size and book-to-market as risk factors to the Capital Asset Pricing Model (CAPM).

Table 8
Cross-sectional Fama–MacBeth regressions — IDIO-LIQ.

	Contemporaneous			One-month-ahead		
	(1)	(2)	(3)	(4)	(5)	(6)
IDIO-LIQ	0.366	0.312	0.194	0.117	0.085	0.067
	(8.72)	(9.15)	(4.95)	(2.83)	(2.86)	(2.71)
BETA		0.012	−0.019		0.021	0.013
		(0.60)	(−14.14)		(0.20)	(1.32)
SIZE		−0.257	−0.067		−0.018	−0.045
		(−7.66)	(−1.69)		(−0.63)	(−1.70)
BM		−1.646	−0.511		0.230	0.218
		(−18.45)	(−8.00)		(3.21)	(3.78)
REV						−0.036
						(−6.58)
MOM			−0.014			0.006
			(−10.75)			(4.18)
IVOL			−0.091			−0.048
			(−51.08)			(−0.79)
MAX			0.083			−0.116
			(68.07)			(−2.19)
I/A			−0.007			−0.003
			(−9.32)			(−4.89)
ROE			0.123			0.141
			(14.15)			(10.80)
LIQU			0.254			0.160
			(10.12)			(3.96)
CVILLIQ			−0.204			0.102
			(−2.02)			(1.76)
SDTURN			−0.243			−0.256
			(−2.45)			(−2.78)
PS			−0.003			0.001
			(−1.56)			(1.46)
BETA1			−0.025			0.192
			(−0.62)			(1.16)
BETA2			−1.123			−4.102
			(−0.25)			(−1.01)
BETA3			−1.576			1.597
			(−1.42)			(1.31)
BETA4			0.024			−0.346
			(0.42)			(−1.24)
SADKAF			−0.003			−0.004
			(−0.90)			(−1.20)
SADKAV			−0.012			−0.017
			(−1.68)			(−1.80)
SUE			0.452			0.343
			(8.67)			(10.28)
VOLDU			−0.052			0.174
			(−3.42)			(8.02)
Intercept	0.013	0.035	−0.025	0.007	0.010	0.012
	(6.09)	(7.92)	(−3.04)	(3.69)	(2.25)	(3.06)
Avg. *R*-squared	0.012	0.100	0.642	0.004	0.045	0.102

This table reports the time series averages of the coefficients from the regressions of contemporaneous and one-month-ahead excess returns on idiosyncratic liquidity using the Fama and MacBeth (1973) methodology. Newey and West (1987) adjusted *t-statistics* are reported.

Columns (5) and (6) ((2) and (3)) present that IDIO-LIQ positively and significantly predicts (explains) one-month-ahead (contemporaneous) stock returns while controlling for various stock characteristics, risk factors, and liquidity-based variables. Both portfolio-level analyses and firm-level cross-sectional regressions show that idiosyncratic liquidity is positively associated with contemporaneous and one-month-ahead stock returns which suggest an at least one-month underreaction to idiosyncratic liquidity.

3.3.4. Underreaction to idiosyncratic liquidity

To better understand the underreaction horizon, I investigate the long-term predictive power of idiosyncratic liquidity by using portfolio sorts and firm-level cross-sectional regressions. Table 9 presents the relevant results. Panel A reports the excess returns and seven-factor alphas generated by IDIO-LIQ sorted quintile portfolios from two to four months after the portfolio formation.

During the second month after portfolio formation, the highest (lowest) IDIO-LIQ quintile portfolio generates a value-weighted excess return of 78 (46) bps. The difference is equal to 32 bps and significant with a *t-statistic* of 3.26. The two-month-ahead seven-factor alpha spread between the extreme quintile portfolios is 32 bps with a *t-statistic* of 3.54. Similarly, the zero-cost strategy has a return of 28 (26) bps excess return (alpha) with a *t-statistic* of 2.98 (2.67) during the third month after portfolio formation.

Table 9
Predictive power of idiosyncratic liquidity.

	Panel A: Long-term portfolio sorts					
	$T + 2$		$T + 3$		$T + 4$	
	RET-RF	alpha	RET-RF	alpha	RET-RF	alpha
High-Low difference	0.32 (3.26)	0.32 (3.54)	0.28 (2.98)	0.26 (2.67)	0.21 (2.53)	0.20 (2.16)
	Panel B: Long-term Fama and MacBeth (1973) regressions					
	$T + 2$		$T + 3$		$T + 4$	
	(1)	(2)	(3)	(4)	(5)	(6)
IDIO-LIQ	0.085 (2.36)	0.092 (2.45)	0.067 (2.00)	0.069 (2.24)	0.049 (1.73)	0.055 (1.86)
Control variables	no	yes	no	yes	no	yes

This table shows the long-term predictive power of idiosyncratic liquidity on future stock returns. Panel A reports the two-months-ahead ($T + 2$), three-months-ahead ($T + 3$), and four-months-ahead ($T + 4$) value-weighted excess return and seven-factor alpha spreads between the highest and the lowest IDIO-LIQ quintile portfolios. Panel B reports the time series averages of the slope coefficients obtained from the univariate and multivariate regressions of two-months-ahead ($T + 2$), three-months-ahead ($T + 3$), and four-months-ahead ($T + 2$) stock returns on idiosyncratic liquidity. Columns (1), (3), and (5) ((2), (4), and (6)) report univariate (multivariate) regression results. Stocks with a price less than $5 are excluded. Newey and West (1987) *t-statistics* are reported in parentheses. The sample period is January 1969–December 2018.

Finally, the four-month-ahead value-weighted alpha spread between the highest and the lowest IDIO-LIQ quintiles is 20 bps with a *t-statistic* of 2.16. According to the portfolio sorts, the predictive power of IDIO-LIQ on future returns is economically and statistically significant for the next four months and becomes insignificant after the fourth month.

Panel B reports time-series averages of the estimated slope coefficients on idiosyncratic liquidity. Columns (1), (3), and (5) report univariate regressions results. Columns (2), (4), and (6) report multivariate regression results where all control variables and liquidity-based variables (BETA, SIZE, BM, REV, MOM, IVOL, MAX, I/A, ROE, LIQU, CVILLIQ, SDTURN, PS, BETA1, BETA2, BETA3, BETA4, SADKAF, SADKAV, SUE, and VOLDU) are simultaneously controlled. Column (1) presents the univariate regression result in which IDIO-LIQ has a significant predictive power on two-month-ahead excess stock return with a coefficient of 0.085 (*t-statistic* = 2.36). When the control variables are added to the regression, the coefficient on idiosyncratic liquidity increases to 0.092. Similarly, as the results in columns (4) and (6) suggest, while controlling for all stock-level characteristics and liquidity-based variables, IDIO-LIQ significantly predicts three-month-ahead and four-month-ahead stock returns. Both portfolio sorts and firm-level cross-sectional regression results suggest that the underreaction to IDIO-LIQ continues for several months in the future, and the positive cross-sectional relationship between IDIO-LIQ and subsequent returns persists for four months.

3.3.5. Possible mechanisms

There are potential channels that might contribute to underreaction to idiosyncratic liquidity. Firm-specific idiosyncratic liquidity is less tangible than well-defined macroeconomic news and firm-level information, such as new products, earnings news, and stock splits. As a result, it is harder to process idiosyncratic liquidity related information especially by average investors. In addition, marginal investors might care less about liquidity, in particular about idiosyncratic liquidity.

Table 6 presents the average characteristics of stocks with low versus high idiosyncratic liquidity. The results document that stocks with high idiosyncratic liquidity have low market capitalization, low institutional holdings, and low analyst coverage that potentially address an investor inattention channel.[20] Analysts tend to provide public information to market participants. Hence, stocks with low analyst coverage are more likely to be the ones where idiosyncratic information moves slower across investors. In addition, institutional investors tend to pay more attention to individual stocks than retail investors due to their expertise and economies of scale in gathering information. This means that stocks with higher institutional ownership tend to receive more investor attention. Moreover, if investors face fixed and high information acquisition costs, then it is expected that information diffuses slower towards small stocks. Hence, investor inattention could trigger the underreaction to idiosyncratic liquidity.

In addition, Table 6 reports a positive coefficient on idiosyncratic volatility. Idiosyncratic volatility (risk) can be considered as a holding cost that prevents traders from exerting price pressure to eliminate mispricing (Pontiff, 1996). Hence, idiosyncratic volatility represents risk that deters arbitrage and results in reduction of mispricing. Stocks with low market capitalization and high market capitalization are considered as costlier stocks to arbitrage. As a result, they are more prone to mispricing (underreaction).

In addition, Baker and Stein (2004) introduce an investor sentiment/market liquidity model in which an unusually liquid market is the one dominated by sentiment-driven irrational investors who tend to underreact to the information. Hence, sentiment-driven overconfident investors might contribute to the underreaction.

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[20] Hirshleifer and Teoh (2003), Peng (2005), Hirshleifer et al. (2013), and Bali et al. (2014) use analyst coverage, institutional holdings, and market capitalization as proxies for investor attention.

Table 10
Robustness checks — portfolio sorts.

	Panel A: Equal-weighted			Panel B: Industrywide			Panel C: Bid–ask spread		
	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q	RET-RF	α_7	α_Q
Low IDIO-LIQ	0.46	−0.21	−0.19	0.45	−0.20	−0.24	0.46	−0.21	−0.18
	(1.91)	(−3.13)	(−2.68)	(1.71)	(−3.13)	(−2.68)	(2.01)	(−2.98)	(−2.58)
2	0.44	−0.12	−0.11	0.48	−0.11	−0.16	0.48	−0.13	−0.14
	(2.02)	(−1.76)	(−1.63)	(2.42)	(−1.66)	(−2.01)	(2.52)	(−1.86)	(−1.98)
3	0.57	−0.03	−0.04	0.58	−0.04	−0.05	0.54	−0.04	−0.01
	(3.01)	(−0.72)	(−1.00)	(3.12)	(−0.92)	(−1.12)	(2.98)	(−0.76)	(−0.08)
4	0.64	0.01	0.01	0.68	0.08	0.10	0.74	0.04	0.05
	(3.19)	(0.27)	(0.10)	(3.62)	(0.92)	(1.22)	(3.29)	(0.58)	(0.65)
High IDIO-LIQ	0.92	0.24	0.28	0.90	0.24	0.22	0.88	0.23	0.23
	(4.07)	(3.54)	(3.67)	(4.12)	(3.54)	(3.67)	(3.98)	(3.42)	(3.57)
High-Low	0.46	0.45	0.48	0.45	0.44	0.46	0.42	0.44	0.41
difference	(4.90)	(4.29)	(4.22)	(4.90)	(4.31)	(4.48)	(4.70)	(4.01)	(3.77)

This table reports returns and alphas generated by idiosyncratic liquidity sorted value-weighted portfolios where idiosyncratic liquidity is constructed using different liquidity measures. Panel A documents portfolio sort results where stock-specific idiosyncratic liquidity is estimated through rolling regressions of stock-specific detrended Amihud illiquidity measure on equal-weighted (EW) detrended market-wide illiquidity measure. Panel B presents returns where idiosyncratic liquidity is calculated through regressions of detrended stock-specific illiquidity on detrended value-weighted market- and industry-wide illiquidity measures. Panel C uses Corwin and Schultz (2012) effective bid–ask spread. Quintile portfolio 1 (5) consists of stocks with the lowest (highest) idiosyncratic liquidity. The last row presents the average monthly return and alpha differences between quintile portfolios 5 (High) and 1 (Low). Newey and West (1987) adjusted *t*-statistics using six lags are reported in parentheses. Stocks with a price less than $5 are excluded. The sample period is from January 1969 to December 2018.

In this subsection, I propose possible mechanisms for underreaction to idiosyncratic liquidity, such as intangible information, investor inattention, costly arbitrage, and investor sentiment. Although I do not examine the channels deeply, future work can investigate the contributions of the aforementioned mechanisms to the underreaction to idiosyncratic liquidity. In addition, it might be interesting to examine which of these mechanisms are stronger in predicting future stock returns.

3.3.6. Robustness check

This subsection provides a battery of robustness checks. Tables 10 and 11 provide robustness test results for three different analyses: (i) equal-weighted market-wide illiquidity measure, (ii) market- and industry-wide illiquidity measure, (iii) and effective bid–ask spread. Table 10 reports returns generated by alternative idiosyncratic liquidity sorted portfolios. Table 11 documents firm-level cross-sectional regression results.

Amihud (2002) and Pastor and Stambaugh (2003) construct a market-wide (il)liquidity measure assigning equal weights to all stocks in the sample. Consistently, I examine whether the positive cross-sectional relation between idiosyncratic liquidity and subsequent returns is robust to the estimation of idiosyncratic liquidity using rolling regressions of firm-specific detrended (il)liquidity on detrended equal-weighted market-wide (il)liquidity.[21] Panel A of Table 10 (column (1) of 11) reports value-weighted returns generated by IDIO-LIQ sorted portfolios (slope coefficients on IDIO-LIQ).

Stocks in the lowest IDIO-LIQ quintile produce a monthly value-weighted excess return of 46 bps, while stocks in the highest IDIO-LIQ quintile portfolio have a monthly value-weighted excess return of 92 bps. As a result, a zero-cost idiosyncratic liquidity strategy, where idiosyncratic liquidity is estimated through rolling regressions of firm-specific illiquidity on equal-weighted market-wide illiquidity, generates 0.46% return per month with a Newey and West (1987) adjusted *t*-statistic of 4.90. In addition, the same strategy generates a value-weighted α_7 (α_Q) of 45 (48) basis points per month with a *t*-statistic of 4.29 (4.22). Outperformance by high IDIO-LIQ stocks and underperformance by low IDIO-LIQ stocks contribute to the positively significant alpha spread between the extreme IDIO-LIQ quintile portfolios. Column (1) of Table 11 documents the multivariate regression result where IDIO-LIQ has a significantly positive coefficient of 0.082 with a *t*-statistic of 2.98.

Chordia et al. (2000) state that an individual asset's liquidity comoves with the market- and industry-wide liquidity. Hence, industry-wide (il)liquidity can explain a significant portion of a stock's liquidity. I examine the cross-sectional relation between idiosyncratic liquidity and future stock returns while accounting for both market- and industry-wide (il)liquidity to estimate each firm's monthly varying idiosyncratic liquidity. More specifically, I estimate the firm-level monthly-varying idiosyncratic (il)liquidity measure from the bivariate monthly rolling regressions of the detrended Amihud (2002) illiquidity measure on the detrended value-weighted market-wide and value-weighted industry-wide illiquidity measures over a 60-month fixed window:

$$d - ILLIQ_{i,t} = \alpha_{i,t} + \beta_{i,t}^{Market} * d - Market - illiquidity_{i,t} + \beta_{i,t}^{Industry} * d - Industry - illiquidity_{i,t} + \epsilon_{i,t}. \tag{9}$$

Idiosyncratic liquidity is equal to the negative sign of the residual term ($\epsilon_{i,t}$). Panel B of Table 10 reports subsequent returns generated by univariate IDIO-LIQ sorted portfolios.[22] Stocks in the highest IDIO-LIQ quintile generate a value-weighted α_7 (α_Q) of

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[21] Stocks under $5 and stocks with less than 15 observations in a given month are excluded to construct equal-weighted market-wide illiquidity measure.

[22] Table 10 reports returns generated by IDIO-LIQ sorted portfolios in which idiosyncratic liquidity is estimated through regressions of firm-specific illiquidity on value-weighted market-wide illiquidity and value-weighted Fama–French-12 industry illiquidity. The positively significant relation between idiosyncratic liquidity and one-month-ahead stock returns is robust to various industry specifications, such as Fama–French-10 and Fama–French-48 industry classifications.

Table 11
Robustness checks — Fama and MacBeth (1973) regressions.

	(1)	(2)	(3)
IDIO-LIQ	0.082	0.071	0.242
	(2.98)	(2.66)	(2.61)
BETA	0.014	0.013	0.011
	(1.46)	(1.42)	(1.08)
SIZE	−0.049	−0.044	−0.047
	(−1.92)	(−1.69)	(−1.80)
BM	0.182	0.168	0.222
	(3.62)	(3.01)	(3.98)
REV	−0.033	−0.048	−0.038
	(−6.58)	(−7.22)	(−6.52)
MOM	0.006	0.05	0.006
	(4.22)	(4.00)	(4.42)
IVOL	−0.052	−0.064	−0.051
	(−1.20)	(−1.40)	(−1.12)
MAX	−0.128	−0.112	−0.110
	(−2.42)	(−2.12)	(−2.22)
I/A	−0.003	−0.003	−0.003
	(−4.52)	(−4.18)	(−4.92)
ROE	0.121	0.128	0.132
	(8.80)	(8.52)	(9.02)
LIQU	0.142	0.180	0.192
	(3.48)	(4.42)	(4.82)
CVILLIQ	0.112	0.118	0.098
	(1.86)	(1.90)	(1.68)
SDTURN	−0.256	−0.266	−0.242
	(−2.70)	(−2.89)	(−2.42)
PS	0.001	0.001	0.001
	(1.62)	(1.48)	(1.56)
BETA1	0.181	0.212	0.201
	(0.97)	(1.00)	(1.22)
BETA2	−3.544	−4.001	−0.389
	(−1.09)	(−1.20)	(−1.12)
BETA3	1.548	1.698	1.413
	(1.19)	(1.41)	(1.18)
BETA4	−0.406	−0.312	−0.401
	(−1.44)	(−1.12)	(−1.43)
SADKAF	−0.003	−0.004	−0.004
	(−1.08)	(−1.41)	(−1.31)
SADKAV	−0.014	−0.018	−0.017
	(−1.78)	(−1.82)	(−1.84)
SUE	0.282	0.317	0.342
	(9.28)	(10.02)	(11.17)
VOLDU	0.186	0.188	0.168
	(9.02)	(8.98)	(8.18)
Intercept	0.011	0.014	0.08
	(2.98)	(3.86)	(2.98)
Avg. R-squared	0.104	0.101	0.098

This table reports the time series averages of the slope coefficients obtained from regressions of one-month-ahead excess stock returns on idiosyncratic liquidity using the Fama and MacBeth (1973) methodology. Column 1 (2) uses detrended equal-weighted market-wide (market- and industry-wide) illiquidity. Column (3) quantifies illiquidity with effective bid–ask spread.

24 (22) bps, whereas stocks in the lowest IDIO-LIQ portfolio have a value-weighted α_7 (α_Q) of −20 (−24) bps per month. As a result, a zero-cost IDIO-LIQ strategy produces 44 (46) bps α_7 (α_Q) per month with a *t-statistic* of 4.31 (4.48). Column (2) of Table 11 documents the regression result where IDIO-LIQ has a positive coefficient of 0.071 with a *t-statistic* of 2.66.

So far, the cross-sectional predictive power of idiosyncratic liquidity on subsequent stock returns is tested using Amihud's 2002 (il)liquidity measure. As a robustness test, I use the effective bid–ask spread (Corwin and Schultz, 2012) as a proxy for illiquidity.[23] More specifically, I examine the cross-sectional predictive power of idiosyncratic liquidity, estimated using rolling regressions of the firm-specific monthly varying detrended effective bid–ask spread on value-weighted detrended market-wide bid–ask spread measure, on stock returns.

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[23] Corwin and Schultz (2012) estimate bid–ask spreads from daily high and low prices. The effective bid–ask spread measure outperforms several low-frequency bid–ask spread estimators.

Consistent with the univariate portfolio-level analyses, Panel C of Table 10 documents that, due to underperformance (outperformance) by stocks in the lowest (highest) IDIO-LIQ quintile, the alpha spread between the extreme IDIO-LIQ quintile portfolios is significantly positive. More specifically, a zero-cost high-low IDIO-LIQ strategy produces 44 (41) bps α_7 (α_Q) per month with a *t-statistic* of 4.01 (3.77). The results in column (3) of Table 11 verify the significantly positive pricing of idiosyncratic liquidity in the cross-section of stock returns.

4. Conclusion

Risk-averse investors demand extra compensation in the form of higher expected return to hold illiquid stocks. The cross-sectional relationship between stock-level illiquidity and returns has been well-documented. Adding to the literature, in this paper, I decompose stock-level illiquidity into three components: (i) intercept, (ii) systematic, and (iii) idiosyncratic.

Firm-level cross-sectional regressions and equal-weighted portfolio-level analyses document that illiquidity alpha, and systematic illiquidity are positively priced only when very small stocks are included. On the other hand, as opposed to the risk-return trade-off, there is a positive (negative) and significant relationship between idiosyncratic (il)liquidity, and contemporaneous and future stock returns. A zero-cost value-weighted idiosyncratic liquidity strategy generates positive and significant risk-adjusted returns for up to four months in the future. This evidence implies that investors tend to underreact to idiosyncratic liquidity. Investor inattention, costly arbitrage, and investor sentiment are possible channels to contribute to the underreaction to idiosyncratic liquidity. Finally, the positively significant cross-sectional relation between idiosyncratic liquidity and subsequent returns is robust to several estimation methods and alternative illiquidity measures.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.finmar.2022.100730.

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