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Arbitrage asymmetry, mispricing and the illiquidity premium

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Abstract

Illiquid assets require a return premium; illiquidity is also a limit-to-arbitrage. We find that Amihud's illiquidity premium is significantly higher among underpriced stocks than among overpriced stocks. Excluding the most mispriced stocks leads to a higher and more reliably estimated illiquidity premium. Amihud's illiquidity measure is positively correlated with overpricing, consistent with arbitrage asymmetry, while inconsistent with Lou and Shu's contention that the return premium associated with the Amihud measure reflects mispricing rather than compensation for illiquidity. Our results demonstrate that it is important to account for their role as limits-to-arbitrage when evaluating the pricing of illiquidity measures.

KEYWORDS

arbitrage asymmetry, illiquidity premium, limits-to-arbitrage

JEL CLASSIFICATION

G10, G11, G14

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1 | INTRODUCTION

Finance theory predicts a positive illiquidity–return relation (e.g., Amihud & Mendelson, 1986).[1] Numerous empirical studies find support for this prediction by using different proxies for liquidity.[2] Arguably the most influential paper in this area is Amihud (2002), who develops an illiquidity measure based on the daily ratio of absolute return to dollar trading volume and finds a significantly positive relation between this illiquidity measure and the cross-section of stock returns. Amihud's (2002) finding has been widely interpreted as evidence consistent with the existence of an illiquidity premium.[3]

More recently, this literature in general, and Amihud (2002) in particular, has been under a considerable amount of scrutiny. Hou et al. (2018) report that 102 out of 106 anomaly variables in the trading friction category, many of which are liquidity variables, fail to exhibit a significant relation with stock returns. Lou and Shu (2017) show that the pricing of the Amihud measure is driven by the trading volume component rather than the ratio of absolute return to trading volume. They also present evidence suggesting that the Amihud premium is caused by mispricing, not by compensation for illiquidity. Amihud and Noh (2021) contend that Lou and Shu (2017) overlooked a term related to the covariance between trading volume and absolute return, and that this term is significantly related to stock returns.

In this paper, we re-examine the illiquidity–return relation by recognizing that illiquidity is also a form of limit-to-arbitrage (Shleifer & Vishny, 1997). To the extent that mispricing exists, it will be more pronounced among more illiquid stocks. That is, everything else being equal, illiquid stocks tend to be more overpriced (or more underpriced) than liquid stocks. This induces a negative illiquidity–return relation among overpriced stocks and a positive illiquidity–return relation among underpriced stocks. Because shorting is more costly than buying, overpricing will be more prevalent than underpricing (Stambaugh et al., 2015). Hence the negative illiquidity–return relation among overpriced stocks will be stronger than the positive illiquidity–return relation among underpriced stocks. The net effect is therefore negative, which reduces the observed illiquidity premium. Studies that do not account for this limit-to-arbitrage effect will tend to understate the true illiquidity premium. The purpose of this study is to test for the above limit-to-arbitrage effect and to quantify the illiquidity premium while controlling for mispricing.

We begin our empirical analysis by sorting all sample stocks based on Amihud's (2002) illiquidity measure. Consistent with prior studies, we find a positive and significant relation between the Amihud measure and the cross-section of stock returns during 1963–2018. Specifically, stocks in the highest-illiquidity quintile outperform those in the lowest illiquidity quintile by 0.34% per month (t statistic = 2.51) in equal-weighted portfolios and by 0.36% per month (t statistic = 2.42) in value-weighted portfolios. Examining Carhart (1997) four-factor alphas, we find that the illiquidity premium remains significant at 0.26% per month (t statistic = 2.75) for equal-weighted portfolios and at 0.17% per month (t statistic = 2.10) for value-weighted portfolios.

[1]Theorists, however, disagree on the magnitude of the illiquidity premium. Constantinides (1986) and Vayanos (1998), for example, argue that transaction costs have only a "second-order" or "very small" effect on stock prices.

[2]See, for example, Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Eleswarapu (1997), Brennan et al. (1998), Chalmers and Kadlec (1998), Datar et al. (1998), Amihud (2002), Chordia et al. (2009) and Hasbrouck (2009).

[3]The literature has used both "liquidity premium" and "illiquidity premium" to refer to the return premium required by investors to hold illiquid assets. We follow Brennan et al. (2013), Amihud et al. (2015) and Amihud and Noh (2021) and use the term "illiquidity premium."

Next, we use double sort to examine whether the observed illiquidity premium varies with mispricing in a manner consistent with the limit-to-arbitrage argument. We follow Stambaugh et al. (2015) and construct a composite mispricing measure based on 11 well-documented anomalies. We independently sort all sample stocks into 5×5 portfolios based on Amihud's illiquidity measure and this mispricing measure. Consistent with the limit-to-arbitrage argument, we find that the observed illiquidity premium is significantly higher among underpriced stocks than among overpriced stocks. Specifically, based on four-factor alphas, the highest-illiquidity quintile outperforms the lowest illiquidity quintile by 0.55% per month (t statistic = 5.39) among the most underpriced stocks, and by only 0.16% per month (t statistic = 1.14) among the most overpriced stocks. The difference in illiquidity premium between the most underpriced and overpriced stocks is 0.39% per month and is statistically significant (t statistic = 2.94). Excluding the most overpriced stocks results in an illiquidity premium of 0.34% per month (t statistic = 3.70), which is significantly higher and more reliably estimated (i.e., higher t statistic) than that for the full sample of stocks (i.e., 0.26% and t statistic = 2.75). Excluding both the most overpriced and the most underpriced stocks is a more conservative approach to purge the effect of mispricing (because overpricing is more prevalent than underpricing), and it leads to an illiquidity premium of 0.30% per month (t statistic = 3.10), which is also higher than that for the full sample of stocks.

The results for value-weighted portfolios are qualitatively similar. We find that the illiquidity premium is 0.47% per month (t statistic = 4.68) for the most underpriced stock quintile and is indistinguishable from zero (0.02% and t statistic = 0.16) for the most overpriced stock quintile. Excluding the most overpriced stocks leads to an illiquidity premium of 0.27% per month (t statistic = 3.44), and excluding the most mispriced stocks leads to an illiquidity premium of 0.23% per month (t statistic = 2.76). These estimates of illiquidity premium are economically larger and statistically more significant than the corresponding number for the full sample of stocks (0.17% and t statistic = 2.10). Overall, we find that the observed illiquidity premium is negatively related to overpricing and that excluding the most mispriced stocks results in a higher and more reliably estimated illiquidity premium. Depending on equal- or value-weighting, the illiquidity premium is 15% or 35% higher after excluding the most mispriced stocks. These results are consistent with the predictions of the limit-to-arbitrage argument.

If overpricing reduces the observed illiquidity premium, as predicted by the limit-to-arbitrage argument, then we should find this effect not only in the cross-section, but also in the time series. That is, we should find lower illiquidity premium during time periods when overpricing is more prevalent. We use investor sentiment to measure the extent of market-wide mispricing over time. Consistent with our prediction, we find that the illiquidity premium is only significant during low-sentiment periods, and is indistinguishable from zero during high-sentiment periods, when overpricing is more prevalent and more severe. This finding further supports the argument that the observed illiquidity premium is inversely related to the degree of overpricing.

We also examine the relation between market-level illiquidity and the illiquidity premium, and the relation between macro uncertainty and the illiquidity premium. We find that the illiquidity premium is much higher and more significant during the period with lower market liquidity, which is consistent with the notion that investors would demand higher returns to hold illiquid assets when the overall market is illiquid. The results are highly significant in both raw returns and risk-adjusted returns, and robust across equal- and value-weighted portfolios. In contrast, the relation between macro uncertainty and the illiquidity premium depends on which benchmark model we use. When we examine the raw returns of the portfolios, we find the illiquidity premium to be slightly higher during the high-uncertainty period. However, when we examine the four-factor alpha of the portfolios, the alpha is higher during the low-uncertainty period.

Lou and Shu (2017) show that the pricing of the Amihud measure is driven by the trading volume component rather than the ratio between absolute return and trading volume. Specifically, they construct a "constant" version of the Amihud measure (i.e., the A_C measure), where the absolute return component is set to 1. They find that the A_C measure is significantly and positively related to the cross-section of stock returns, whereas the residual from regressions of the Amihud measure on the A_C measure is negatively related to stock returns. We are able to confirm this finding of Lou and Shu (2017) in our sample.

Lou and Shu also contend that the trading volume premium, and by extension the premium associated with the Amihud measure, is caused by mispricing, not by compensation for illiquidity. We perform a direct test of this contention by relating the Amihud measure and the A_C measure to our composite mispricing measure. If the positive Amihud–return relation is due to mispricing, then we should find stocks with a high Amihud measure (or a high A_C measure) to be relatively undervalued (thereby earning high subsequent returns). We find the opposite. That is, stocks with a high Amihud illiquidity measure or a high A_C measure tend to be overvalued rather than undervalued based on our mispricing measure. This finding does not support the mispricing-based interpretation of the Amihud premium. It is, however, consistent with the arbitrage asymmetry argument, which predicts that illiquid stocks are more likely to be overpriced than underpriced because shorting is more costly than buying (i.e., overpricing is more difficult to arbitrage away.)

To find out which component(s) of the Amihud measure drive our results, we follow Amihud and Noh (2021) and decompose the Amihud measure into three terms—the absolute return, the inverse dollar trading volume and the covariance between the first two terms. We then perform double sort based on each component and the mispricing measure to see if the main results still hold (i.e., asymmetric illiquidity premiums between underpriced and overpriced stocks). We find that three components yield qualitatively similar results. That is, the observed illiquidity premium is higher among underpriced stocks than among overpriced stocks no matter which component we use to measure stocks' illiquidity.

Our paper contributes to the extensive literature on illiquidity premium. Illiquid assets require a return premium. This is rational, not driven by mispricing. However, illiquidity is also a form of limits-to-arbitrage, and it induces a positive (negative) illiquidity–return relation among underpriced (overpriced) stocks. Arbitrage asymmetry implies that the overall impact is negative, reducing the observed illiquidity premium. To the best of our knowledge, this is the first paper that tests and controls for this limit-to-arbitrage effect when estimating illiquidity premium. Consistent with our predictions, we find that the illiquidity premium is significantly higher among underpriced stocks than among overpriced stocks. Similarly, the illiquidity premium is significant only during low-sentiment periods and nonexistent during high-sentiment periods. Excluding the most overpriced or the most mispriced stocks results in a higher and more reliably estimated illiquidity premium. Our results demonstrate that it is important to account for their roles as limits-to-arbitrage when evaluating the pricing of illiquidity measures.[4]

Our paper adds to the recent debate on the sources and interpretation of the positive Amihud measure–return relation. Lou and Shu (2017) show that the pricing of the Amihud measure is driven by the trading volume component, and not by the ratio of absolute return to trading volume. Moreover, they present evidence implying that the return premium associated with the Amihud measure is caused by mispricing, rather than compensation for illiquidity.

[4]Our paper is also related to recent studies on the interactive and asymmetric relations in empirical finance (e.g., Cong et al., 2023; Jarrow et al., 2020).

Amihud and Noh (2021) challenge Lou and Shu's finding. They show that Lou and Shu (2017) missed a term related to the covariance between trading volume and absolute return, and that this term has significant effects on stock returns. Amihud and Noh (2021) also show that the pricing of the Amihud measure is robust to the control of a mispricing measure.[5] In our paper, we are able to confirm Lou and Shu's result that the constant version of the Amihud measure (i.e., the A_C measure) is significantly and positively related to stock returns, whereas the residual Amihud measure is not. However, we find that both the Amihud measure and the A_C measure are positively related to our composite mispricing measure, suggesting that stocks with a high Amihud measure or A_C measure are more overpriced. This finding is contrary to the contention that the return premium associated with the Amihud measure is due to mispricing.

The rest of our paper proceeds as follows. Section 2 presents the data, sample and descriptive statistics. Section 3 presents the empirical results. Section 4 presents additional analyses. Section 5 concludes.

2 | DATA, SAMPLE AND DESCRIPTIVE STATISTICS

2.1 | Data and sample

We obtain stock data from Center for Research in Security Prices (CRSP) and accounting data from Compustat. Our sample consists of common stocks (with a CRSP share code of 10 or 11) traded on New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers Automated Quotations (NASDAQ). When a firm is delisted from an exchange, we replace any missing returns with the delisting returns provided by CRSP. Our sample period is from August 1963 to December 2018. We obtain Fama and French (1993) factors and the momentum factor from Kenneth French's website.[6]

2.2 | The Amihud illiquidity measure

We follow many prior studies (e.g., Lou & Shu, 2017) and use Amihud's (2002) illiquidity measure, which is defined as follows:

$$\text{Amihud}_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|r_{id}|}{\text{Dvol}_{id}}, \tag{1}$$

where $|r_{id}|$ is the absolute value of return of stock i on day d, Dvol_{id} is the dollar trading volume of stock i on day d, and D_{it} is the number of trading days (with nonzero absolute return to dollar volume ratio) for stock i in month t.[7] We require a stock to have at least 10 days of

[5]This finding is consistent with ours, but Amihud and Noh (2021) do not directly examine the link between Amihud's illiquidity measure and their mispricing measure.

[6]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[7]The NASDAQ trading volume is inflated during part of our sample period. We follow Gao and Ritter (2010) and Hou et al. (2018) to adjust the NASDAQ trading volume as follows. Before February 1, 2001, we divide the volume of NASDAQ stocks by two. From February 1, 2001 to December 31, 2001, we divide NASDAQ volume by 1.8. For 2002 and 2003, we divide NASDAQ volume by 1.6. For 2004 and later years, we do not adjust the volume of NASDAQ stocks.

nonzero volume and return data to compute the Amihud measure for month t. We multiply the Amihud illiquidity measure by 10^6 and winsorize at the 1st and 99th percentiles in each cross-section to minimize the impact of outliers. We follow Lou and Shu (2017) and use the monthly illiquidity measure in our analyses because it reflects more recent information.[8] To minimize microstructure effects, we follow Brennan et al. (2013), Lou and Shu (2017) and Amihud and Noh (2021) and skip a month after constructing the Amihud measure. That is, we match the illiquidity measure of month $t-2$ to stock returns in month t. To minimize the impact of low-priced stocks, we follow the previous literature and remove a stock-month if the stock price is lower than $5 at the end of month when the Amihud measure is calculated.

2.3 | The mispricing measure

We follow Stambaugh et al. (2015) and construct a mispricing measure based on the following 11 stock market anomalies that cannot be explained by the Fama and French (1993) three-factor model:

1. Financial Distress (Campbell et al., 2008),
2. O-score Bankruptcy Probability (Ohlson, 1980),
3. Net Stock Issues (Fama & French, 2008; Loughran & Ritter, 1995; Ritter, 1991),
4. Composite Equity Issues (Daniel & Titman, 2006),
5. Total Accruals (Sloan, 1996),
6. Net Operating Assets (Hirshleifer et al., 2004),
7. Momentum (Jegadeesh & Titman, 1993),
8. Gross Profitability (Novy-Marx, 2013),
9. Asset Growth (Cooper et al., 2008),
10. Return on Assets (Chen et al., 2010; Fama & French, 2006),
11. Investment-to-Assets (Titman et al., 2004, Xing, 2008).

We follow Stambaugh et al. (2015) and combine the above anomalies to produce a single measure of mispricing. While each anomaly itself is a mispricing measure, combining them diversifies away some noise in each individual anomaly and thereby increases the precision of the mispricing measure. For each of the above anomalies, we assign a percentile rank to each stock based on the given anomaly variable. The higher (lower) ranks are assigned to stocks that are expected to generate lower (higher) average abnormal returns based on the findings of prior literature. Taking the momentum anomaly as an example, past winners will be assigned lower ranks than past losers. In contrast, for the asset growth anomaly, low-asset growth stocks will be given lower ranks than high-asset growth stocks because prior studies (Cooper et al., 2008) have shown that low-asset growth firms earn significantly higher returns than high-asset growth firms. We then construct the mispricing measure for each stock as the average of the percentile ranks across all 11 anomalies.[9] The stocks with the highest values of this measure are the most "overpriced" and those with the lowest values are the most "underpriced." Therefore, this measure can be considered as an overpricing measure. As in Stambaugh et al. (2015), we note that this mispricing measure is purely cross-sectional, that is, it denotes only relative overpricing.

[8]Our results are qualitatively the same if we use the annual Amihud measure based on the past 12 months of data.
[9]We require that the stocks have nonmissing percentile ranks at the end of a month for at least five anomalies.

2.4 | Summary statistics

Panel A of Table 1 presents the summary statistics of the Amihud measure and several stock characteristics including firm size, book-to-market ratio and past returns. Firm size is the market capitalization at the end of the previous year. Book-to-market ratio is the ratio of the book value of equity to the market value of equity, where the book value of equity is defined as stockholders' equity plus balance-sheet deferred taxes and investment tax credit, minus the book value of preferred stock. Past returns include the past 1-month return and the past 1-year (excluding the most recent month) return. We find that the average Amihud measure is significantly larger than its median, suggesting that the Amihud measure is skewed to the right. The average market capitalization of our sample stocks is $3.913 billion. The average book-to-market ratio is close to 0.82. The average past 1-month return is 1.12%, while the average past 1-year return is 16.09%.

TABLE 1 Summary statistics.

This table reports the summary statistics. We obtain stock data from the CRSP and accounting data from Compustat. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2018. Amihud is the Amihud (2002) measure, defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in a month. Ret[−12, −2] is the cumulative stock return from month $t-12$ to $t-2$, and Ret[−1] is the stock return in month $t-1$. ME is the firm's market capitalization at the end of the previous year, measured in millions of dollars. B/M is the book-to-market ratio calculated as a firm's book value of equity divided by the firm's market capitalization. The Amihud measure and B/M are winsorized at the 1st and 99th percentiles in each cross-section. The Amihud measure is multiplied by 10^6. Panel A reports the summary statistics of the stock characteristic variables and Panel B reports the correlations among these variables.

Panel A: Summary statistics

	Mean	P10	P25	P50	P75	P90
Amihud	0.4695	0.0078	0.0237	0.1008	0.4024	1.2456
Ret[−12, −2]	0.1609	−0.2123	−0.0625	0.1059	0.3074	0.5661
Ret[−1]	0.0112	−0.0920	−0.0424	0.0066	0.0586	0.1177
ME	3912.85	93.48	274.16	841.32	2650.81	8359.44
B/M	0.8210	0.2627	0.4499	0.7201	1.0576	1.4743

Panel B: Correlations

	Amihud	Ret[−12, −2]	Ret[−1]	ME	B/M
Amihud	1.0000				
Ret[−12, −2]	−0.0704	1.0000			
Ret[−1]	0.0000	0.0191	1.0000		
ME	−0.0965	−0.0098	−0.0047	1.0000	
B/M	0.2332	−0.0850	0.0157	−0.1170	1.0000

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

Panel B of Table 1 presents the correlations among these variables. We first calculate cross-sectional correlation coefficients among the variables in each month and then report the time-series averages. We find that the Amihud measure is negatively correlated with firm size and past 1-year return, and positively correlated with the book-to-market ratio. These results suggest that small firms, past losers and value firms tend to be more illiquid.

Next, we verify the validity of our mispricing measure by using a portfolio approach. Each month we divide all sample stocks into five quintile portfolios based on our mispricing measure, form equal- and value-weighted portfolios, and then hold the portfolios for 1 month. If our mispricing measure indeed captures (relative) overpricing, then we would expect the most overpriced stocks to earn significantly lower subsequent returns than the most underpriced stocks. We examine both equal- and value-weighted portfolios. In addition to raw returns, we also estimate CAPM one-factor alpha, Fama–French three-factor alpha and Carhart four-factor alpha by running the following time-series regressions:

$$\begin{aligned} r_{i,t} &= \alpha_i + \beta_i \mathrm{MKT}_t + e_{i,t}, \\ r_{i,t} &= \alpha_i + \beta_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + e_{i,t}, \\ r_{i,t} &= \alpha_i + \beta_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + u_i \mathrm{UMD}_t + e_{i,t}, \end{aligned} \tag{2}$$

where $r_{i,t}$ is the return for portfolio i in month t, MKT, SMB, HML and UMD are market, size, value and momentum factors (Carhart, 1997; Fama & French, 1993), and $e_{i,t}$ is the regression residual.

Panel A of Table 2 reports the results for equal-weighted portfolios. We find strong evidence that the most overpriced stocks significantly underperform the most underpriced stocks. The return spread is 0.88% per month and highly significant with a t statistic of 8.92. The results for one-, three- and four-factor alphas are qualitatively similar; the most overpriced stocks underperform the most underpriced stocks by 0.98%, 1.05% and 0.76% per month, respectively, all of which are highly statistically significant. The results for value-weighted portfolios (reported in Panel B) are quantitatively lower but qualitatively similar. The most overpriced stocks underperform the most underpriced stocks by 0.55%, 0.69%, 0.51% and 0.86% per month for raw returns, one-, three- and four-factor alpha, respectively. The t statistics for the return spread are all greater than 4. Overall, the results in Table 2 are consistent with Stambaugh et al. (2015) and lend strong support to our mispricing measure.

3 | EMPIRICAL RESULTS

3.1 | Single sort

We begin our analysis of the illiquidity premium by sorting all sample stocks into quintile portfolios at the end of each month based on the previous month Amihud's illiquidity measure.[10] We construct both equal- and value-weighted portfolios and hold the portfolios for 1 month. We compute returns for each illiquidity-sorted portfolio as well as the return difference between the most illiquid and most liquid portfolios. Table 3 presents the results.

[10]As stated earlier, we follow Amihud (2002) and Lou and Shu (2017) and skip a month after constructing the Amihud measure before forming portfolios to minimize the microstructure effect.

TABLE 2 Mispricing measure and the cross-section of stock returns.

This table reports the raw returns and alphas of portfolios formed by sorting stocks on our mispricing measure. We obtain stock data from the CRSP. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than \$5. Our sample period is from August 1963 to December 2018. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. We sort all sample stocks into quintiles based on the mispricing measure at the end of each month, construct equal-weighted as well as value-weighted portfolios and hold the portfolios for 1 month. We obtain Fama and French (1993) three factors and the momentum factor from Kenneth French's website. The t statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Most underpriced	Q2	Q3	Q4	Most overpriced	Q1–Q5
Panel A: Equal-weighted returns						
Raw return	1.48	1.32	1.22	1.04	0.60	0.88
	(7.33)	(6.51)	(5.81)	(4.69)	(2.34)	(8.92)
α_1	0.57	0.40	0.29	0.09	−0.41	0.98
	(5.93)	(4.24)	(2.93)	(0.97)	(−3.45)	(11.18)
α_3	0.45	0.24	0.11	−0.10	−0.60	1.05
	(9.60)	(5.63)	(2.53)	(−2.20)	(−8.39)	(12.18)
α_4	0.40	0.23	0.15	0.00	−0.36	0.76
	(8.15)	(5.08)	(3.38)	(0.02)	(−5.97)	(10.26)
Panel B: Value-weighted returns						
Raw return	1.04	0.98	0.91	0.74	0.49	0.55
	(6.42)	(5.63)	(5.20)	(3.60)	(2.03)	(4.08)
α_1	0.20	0.10	0.03	−0.19	−0.50	0.69
	(4.62)	(2.48)	(0.54)	(−3.16)	(−5.37)	(5.64)
α_3	0.16	0.10	0.00	−0.19	−0.35	0.51
	(4.23)	(2.41)	(0.02)	(−3.37)	(−4.50)	(5.09)
α_4	0.26	0.12	−0.03	−0.28	−0.60	0.86
	(6.67)	(3.06)	(−0.88)	(−4.98)	(−6.87)	(7.66)

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

Consistent with prior literature, we find a significantly positive illiquidity premium during our sample period 1963–2018. Specifically, stocks in the highest-illiquidity quintile outperform those in the lowest illiquidity quintile by 0.34% per month (t statistic = 2.51) in equal-weighted portfolios and by 0.36% per month (t statistic = 2.42) in value-weighted portfolios.

Examining four-factor alphas, we find that the illiquidity premium remains significant at 0.26% per month (t statistic = 2.75) for equal-weighted portfolios and at 0.17% per month (t statistic = 2.10) for value-weighted portfolios. In addition to the four-factor alpha, we also

TABLE 3 Illiquidity and the cross-section of stock returns.

This table reports the raw returns and alphas of portfolios formed by sorting stocks on the Amihud measure. We obtain stock data from the CRSP. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2018. The Amihud measure is defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in a month. We sort all sample stocks into quintiles at the end of each month based on the previous month Amihud's illiquidity measure. We construct equal-weighted as well as value-weighted portfolios and hold the portfolios for 1 month. We compute returns for each illiquidity-sorted portfolio as well as the return difference between the most illiquid and most liquid portfolios. We obtain Fama and French (1993) three factors and the momentum factor from Kenneth French's website. The *t* statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Lowest illiquidity	2	3	4	Highest illiquidity	High–low
Panel A: Equal-weighted returns						
Raw return	0.96	1.07	1.14	1.18	1.30	0.34
	(5.09)	(4.96)	(4.96)	(5.02)	(5.48)	(2.51)
α_4	0.01	0.03	0.05	0.07	0.26	0.26
	(0.18)	(0.63)	(1.03)	(1.41)	(3.05)	(2.75)
β_{mkt}	1.05	1.09	1.05	0.98	0.78	−0.27
	(91.98)	(79.60)	(69.13)	(58.90)	(24.07)	(−7.97)
β_{smb}	0.09	0.51	0.79	0.88	0.83	0.74
	(2.64)	(12.75)	(15.83)	(15.01)	(8.78)	(9.42)
β_{hml}	0.08	0.12	0.21	0.35	0.40	0.32
	(2.43)	(3.05)	(6.48)	(8.51)	(6.24)	(5.62)
β_{mom}	−0.02	−0.07	−0.09	−0.11	−0.08	−0.05
	(−1.23)	(−3.13)	(−4.03)	(−3.56)	(−1.36)	(−1.06)
Panel B: Value-weighted returns						
Raw return	0.87	1.03	1.09	1.11	1.22	0.36
	(5.10)	(5.22)	(5.25)	(5.17)	(5.47)	(2.42)
α_4	0.01	0.04	0.04	0.04	0.18	0.17
	(0.98)	(0.89)	(0.83)	(0.79)	(2.26)	(2.10)
β_{mkt}	0.99	1.04	0.99	0.92	0.80	−0.19
	(289.48)	(93.81)	(79.84)	(59.22)	(29.32)	(−6.88)
β_{smb}	−0.17	0.33	0.63	0.73	0.75	0.92
	(−25.72)	(11.81)	(16.87)	(15.66)	(9.11)	(11.14)
β_{hml}	−0.02	0.14	0.25	0.35	0.41	0.43
	(−3.02)	(3.89)	(7.62)	(9.21)	(7.14)	(7.40)
β_{mom}	0.01	−0.06	−0.07	−0.09	−0.06	−0.07
	(2.33)	(−2.75)	(−3.49)	(−3.27)	(−1.12)	(−1.38)

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

report the loadings in the market, size, value and momentum factors to examine whether stocks with different levels of illiquidity load differently on these factors. The results indicate that the most illiquid stocks tend to have lower loadings on MKT and higher loadings on SMB and HML than the most liquid stocks. The higher SMB and HML loadings for the most illiquid stocks are consistent with the summary statistics reported in Table 1, which indicate that stocks with higher Amihud's illiquidity measure tend to be smaller and have higher book-to-market ratios. Because small and value firms tend to have higher average returns, controlling for SMB and HML results in a smaller performance difference between the most illiquid stocks and the most liquid stocks. This explains why the illiquidity premium is lower when measured in four-factor alphas than in raw returns.

3.2 | Double sort

Next, we use double sort to examine whether the illiquidity premium varies negatively with the degree of overpricing, as predicted by the limit-to-arbitrage argument. As stated earlier, we follow Stambaugh et al. (2015) and construct a composite mispricing measure based on 11 well-documented anomalies. We then independently sort all sample stocks into 5×5 portfolios based on Amihud's illiquidity measure and our mispricing measure. We form portfolios at the end of each month using the previous month illiquidity measure and the mispricing measure and hold the portfolios for 1 month. Table 4 presents the results. We report the results for both raw returns and four-factor alphas and for both equal-weighted portfolios (Panel A) and value-weighted portfolios (Panel B).

Consistent with the limit-to-arbitrage argument, we find that the observed illiquidity premium is significantly higher among underpriced stocks than among overpriced stocks. In Panel A, for example, the highest-illiquidity quintile outperforms the lowest illiquidity quintile by 0.62% per month (t statistic = 4.34) among the most underpriced stocks (Q5), and by only 0.31% per month (t statistic = 1.83) among the most overpriced stocks (Q1). The difference in the illiquidity premium between the most underpriced stocks and most overpriced stocks is 0.31% per month, and statistically significant with a t statistic of 2.14.

Because overpricing is more likely than underpricing due to short-sale constraints (Stambaugh et al., 2015), we remove the most overpriced stocks (Q1) and re-estimate the illiquidity premium by using stocks in Q2–Q5. We find that excluding the most overpriced stocks results in an illiquidity premium of 0.41% per month (t statistic = 3.08), which is higher than that for the full sample (0.34% and t statistic = 2.51) and is more reliably estimated (i.e., has higher t statistics). In an untabulated test, we find that the difference of 0.07% per month between these two illiquidity premium estimates is statistically significant with a t statistic of 3.77.

We also re-estimate the illiquidity premium by excluding both the most overpriced stocks and the most underpriced stocks. This is a more conservative approach to purge the limit-to-arbitrage effect because overpricing is supposed to be more prevalent and more severe than underpricing (Stambaugh et al., 2015). To obtain a clean picture of the illiquidity premium, ideally one should remove all mispriced stocks, the majority of which should be overpriced stocks. Nonetheless, excluding both Q1 and Q5 leads to an illiquidity premium of 0.37% per month (t statistic = 2.76), which is also higher than that for the full sample.[11]

[11]However, the difference between 0.37% and 0.34% is statistically insignificant with a t statistic of 1.01.

TABLE 4 Illiquidity, mispricing and the cross-section of stock returns.

This table reports the raw returns and four-factor alphas of portfolios formed by sorting stocks independently on the Amihud measure and our mispricing measure. We obtain stock data from the CRSP. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2018. The Amihud measure is defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in a month. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. We construct equal-weighted as well as value-weighted portfolios at the end of each month and hold the portfolios for 1 month. We obtain Fama and French (1993) three factors and the momentum factor from Kenneth French's website. The *t* statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Lowest illiquidity	**2**	**3**	**4**	**Highest illiquidity**	**High–low**
Panel A: Equal-weighted returns						
Raw return						
Q1 (overpriced)	0.42	0.55	0.63	0.68	0.73	0.31
	(1.68)	(2.09)	(2.31)	(2.48)	(2.79)	(1.83)
Q2	0.83	1.00	1.05	1.17	1.18	0.36
	(3.86)	(4.38)	(4.45)	(4.80)	(4.87)	(2.36)
Q3	1.00	1.19	1.23	1.31	1.36	0.36
	(5.20)	(5.76)	(5.39)	(5.75)	(5.75)	(2.64)
Q4	1.07	1.24	1.45	1.31	1.52	0.45
	(5.89)	(6.07)	(6.57)	(5.87)	(6.71)	(3.24)
Q5 (underpriced)	1.18	1.35	1.46	1.59	1.80	0.62
	(6.86)	(6.72)	(6.64)	(7.04)	(7.93)	(4.34)
Q5–Q1	0.76	0.80	0.83	0.92	1.06	0.31
	(5.45)	(6.41)	(6.74)	(7.82)	(11.24)	(2.14)
Q2–Q5	1.04	1.19	1.29	1.34	1.45	0.41
	(5.73)	(5.76)	(5.80)	(5.89)	(6.31)	(3.08)
Q2–Q4	0.99	1.14	1.24	1.26	1.35	0.37
	(5.16)	(5.43)	(5.47)	(5.50)	(5.82)	(2.76)
Four-factor alpha						
Q1 (overpriced)	−0.44	−0.37	−0.37	−0.37	−0.28	0.16
	(−4.38)	(−4.53)	(−5.11)	(−5.00)	(−2.45)	(1.14)
Q2	−0.11	−0.05	−0.03	0.05	0.14	0.25
	(−1.62)	(−0.75)	(−0.52)	(0.82)	(1.51)	(2.20)
Q3	0.01	0.13	0.10	0.19	0.32	0.31
	(0.21)	(2.04)	(1.57)	(3.07)	(3.41)	(2.85)

TABLE 4 (Continued)

	Lowest illiquidity	2	3	4	Highest illiquidity	High–low
Q4	0.09	0.16	0.28	0.14	0.48	0.39
	(1.75)	(2.99)	(4.17)	(2.36)	(4.43)	(3.34)
Q5 (underpriced)	0.20	0.26	0.33	0.47	0.75	0.55
	(3.81)	(4.28)	(4.63)	(5.97)	(8.27)	(5.39)
Q5–Q1	0.64	0.64	0.70	0.84	1.03	0.39
	(5.56)	(6.57)	(7.01)	(8.47)	(11.05)	(2.94)
Q2–Q5	0.08	0.12	0.16	0.20	0.41	0.34
	(1.83)	(2.70)	(3.28)	(3.96)	(4.92)	(3.70)
Q2–Q4	0.02	0.08	0.11	0.13	0.32	0.30
	(0.33)	(1.67)	(2.08)	(2.49)	(3.61)	(3.10)
Panel B: Value-weighted returns						
Raw return						
Q1 (overpriced)	0.44	0.62	0.69	0.69	0.67	0.23
	(1.80)	(2.51)	(2.75)	(2.73)	(2.72)	(1.34)
Q2	0.68	0.94	1.02	1.03	1.13	0.45
	(3.32)	(4.41)	(4.68)	(4.54)	(4.87)	(2.74)
Q3	0.85	1.10	1.18	1.22	1.26	0.40
	(4.92)	(5.69)	(5.55)	(5.91)	(5.47)	(2.68)
Q4	0.93	1.17	1.28	1.24	1.39	0.46
	(5.30)	(6.18)	(6.38)	(5.96)	(6.47)	(2.92)
Q5 (underpriced)	1.00	1.23	1.31	1.45	1.70	0.69
	(6.18)	(6.67)	(6.57)	(7.15)	(7.58)	(4.21)
Q5–Q1	0.56	0.61	0.61	0.76	1.02	0.47
	(3.74)	(5.11)	(5.25)	(6.58)	(10.07)	(2.99)
Q2–Q5	0.91	1.11	1.19	1.22	1.37	0.46
	(5.46)	(5.80)	(5.91)	(5.93)	(6.23)	(3.15)
Q2–Q4	0.85	1.07	1.15	1.16	1.26	0.40
	(4.84)	(5.47)	(5.59)	(5.54)	(5.69)	(2.78)
Four-factor alpha						
Q1 (overpriced)	−0.36	−0.27	−0.28	−0.33	−0.34	0.02
	(−3.70)	(−3.24)	(−3.73)	(−4.33)	(−3.17)	(0.16)
Q2	−0.22	−0.05	−0.02	−0.04	0.09	0.32
	(−3.25)	(−0.83)	(−0.40)	(−0.52)	(0.99)	(2.78)
Q3	−0.03	0.09	0.10	0.16	0.21	0.24
	(−0.53)	(1.39)	(1.37)	(2.47)	(2.04)	(2.08)

(Continues)

TABLE 4 (Continued)

	Lowest illiquidity	2	3	4	Highest illiquidity	High–low
Q4	0.08	0.14	0.16	0.12	0.34	0.26
	(1.60)	(2.42)	(2.44)	(1.76)	(3.56)	(2.50)
Q5 (underpriced)	0.14	0.21	0.23	0.39	0.61	0.47
	(3.25)	(3.60)	(3.55)	(5.25)	(6.58)	(4.68)
Q5–Q1	0.50	0.47	0.51	0.72	0.95	0.45
	(4.14)	(4.91)	(5.28)	(7.11)	(8.98)	(3.05)
Q2–Q5	0.04	0.09	0.11	0.14	0.31	0.27
	(2.74)	(2.06)	(2.26)	(2.67)	(4.03)	(3.44)
Q2–Q4	−0.02	0.06	0.07	0.08	0.21	0.23
	(−0.65)	(1.16)	(1.32)	(1.40)	(2.58)	(2.76)

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

An examination of four-factor alphas reveals qualitatively similar results. We find that the illiquidity premium is 0.55% per month (t statistic = 5.39) among the most underpriced stocks, but only 0.16% per month (t statistic = 1.14) among the most overpriced stocks. The difference of 0.39% is statistically significant with a t statistic of 2.94. Excluding the most overpriced stocks leads to an illiquidity premium of 0.34% per month (t statistic = 3.70), significantly higher and more reliably estimated than that for the full sample (0.26%, t statistic = 2.75). Excluding both the most overpriced and most underpriced stocks leads to an illiquidity premium of 0.30% per month (t statistic = 3.10), which is also higher, although not significantly so, than that for the full sample.

In Panel B, we find qualitatively similar results for value-weighted portfolios. Using raw returns, we find that the illiquidity premium is 0.69% per month (t statistic = 4.21) among the most underpriced stock quintile, and only 0.23% per month (t statistic = 1.34) among the most overpriced stocks. The difference of 0.47% per month is economically large and statistically significant with a t statistic of 2.99. Excluding the most overpriced stocks results in an illiquidity premium at 0.46% per month (t statistic = 3.15), and excluding both the most overpriced and most underpriced stocks leads to an illiquidity premium of 0.40% per month (t statistic = 2.78). Both illiquidity premium estimates are higher and have larger t statistics than the illiquidity premium for the full sample of stocks reported in Table 3 (i.e., 0.36% per month with a t statistic of 2.42).

Examining four-factor alphas, we find that the illiquidity premium is 0.47% per month (t statistic = 4.68) among the most underpriced stock quintile, and 0.02% per month (t statistic = 0.16) among the most overpriced stocks. The difference of 0.45% per month is economically large and statistically significant with a t statistic of 3.05. Excluding the most overpriced stocks results in an illiquidity premium at 0.27% per month (t statistic = 3.44), and excluding both the most overpriced and most underpriced stocks leads to an illiquidity premium of 0.23% per month (t statistic = 2.76). Both of these estimates are economically larger and statistically more significant than that for the full sample of stocks (0.17%, t statistic = 2.10).

Figure 1 contains a graphical representation of our main results. Specifically, we plot the illiquidity premium across mispricing quintiles for equal-weighted portfolios (Panel A) and value-weighted portfolios (Panel B). The blue bars represent raw returns while the orange bars

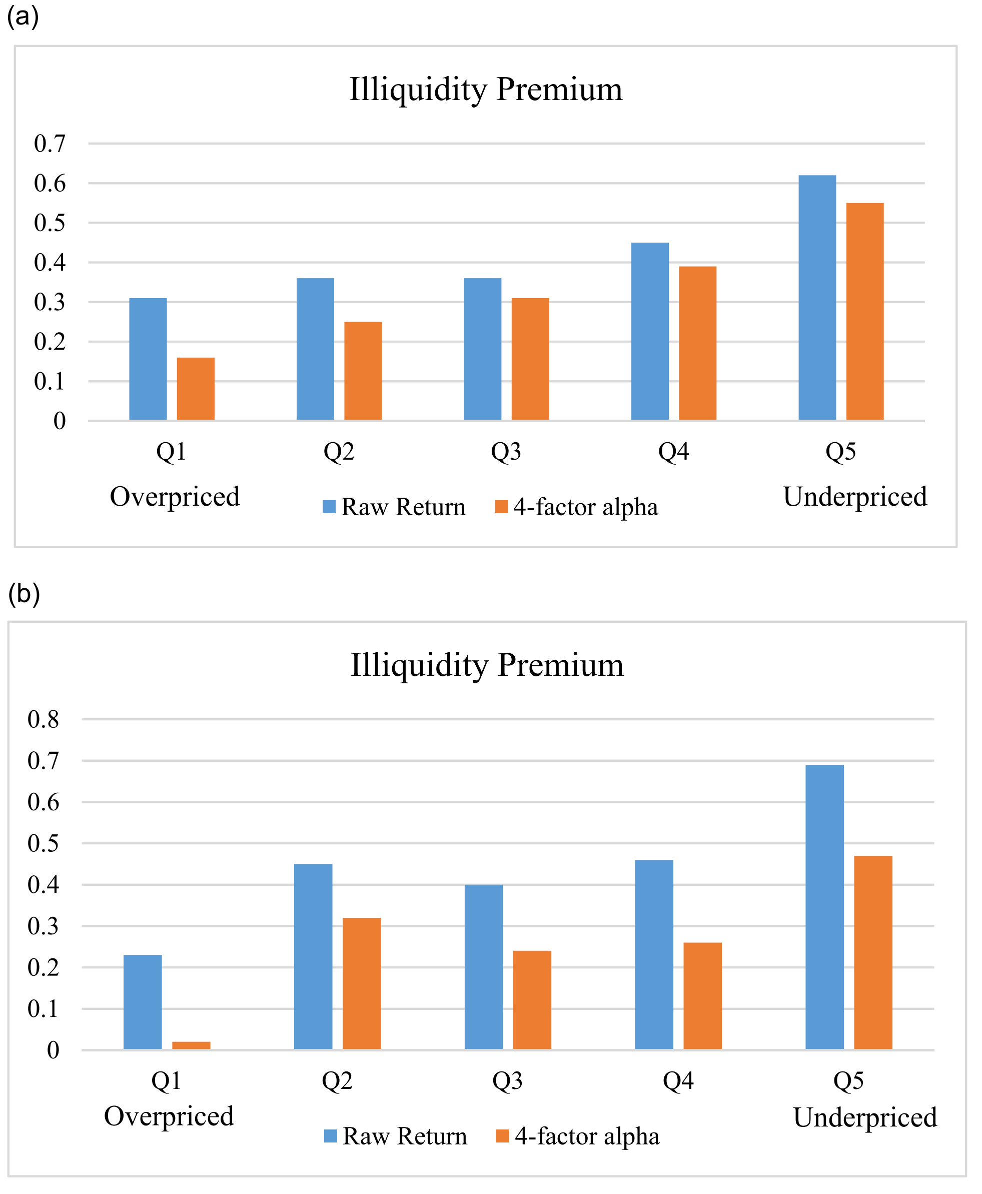

FIGURE 1 Illiquidity premium across mispricing quintiles. This figure presents the illiquidity premium across mispricing quintiles. The mispricing measure is the arithmetic average of each stock's percentile rank for 11 anomalies described in Section 2.3. We construct equal-weighted portfolios as well as value-weighted portfolios at the end of each month based on the Amihud measure and the mispricing measure and hold the portfolios for 1 month. The illiquidity premium is expressed as percent per month. The sample period is 1963–2018. (a) Equal-weighted portfolios and (b) value-weighted portfolios. [Color figure can be viewed at wileyonlinelibrary.com]

correspond to four-factor alphas. It is evident that in each panel the illiquidity premium, whether measured in raw returns or four-factor alphas, increases almost monotonically from the most overpriced quintile (Q1) to the most underpriced quintile (Q5). In addition, the figure shows that the difference between Q5 and Q1 is economically large.

Overall, our double-sort analysis reveals strong evidence that the observed illiquidity premium is significantly lower among overpriced stocks than among underpriced stocks. In fact, the illiquidity premium among most overpriced stocks is indistinguishable from zero. Excluding the most mispriced stock results in higher and statistically more reliable estimates of the illiquidity premium. Depending on the specific performance measure and portfolio weighting scheme, the illiquidity premium is between 9% and 35% higher after excluding the most mispriced stocks. These findings are consistent with the predictions of the limit-to-arbitrage argument.

3.3 | Fama–MacBeth regressions

In this section, we use a regression approach to examine the illiquidity–return relation and the effect of overpricing on this relation. Specifically, we estimate the following cross-sectional regression:

$$\begin{aligned} r_{i,t} = \alpha &+ \beta_1 \ln(\text{Amihud})_{i,t-2} + \beta_2 \text{Mispricing}_{i,t-1} + \beta_3 \ln(\text{Amihud})_{i,t-2} \\ &\times \text{Mispricing}_{i,t-1} + \beta_4 \text{Ret}[-12,-2]_{i,t} + \beta_5 \text{Ret}[-1]_{i,t} + \beta_6 \ln(\text{ME}_{i,t-1}) \\ &+ \beta_7 \text{BM}_{i,t-1} + e_{i,t}. \end{aligned} \tag{3}$$

We follow prior literature (e.g., Brennan et al., 1998; Lou & Shu, 2017) and use the Fama and French three-factor adjusted stock returns as the dependent variable. A primary independent variable of interest is the Amihud measure. A positive and significant coefficient on the Amihud measure would be consistent with the existence of an illiquidity premium. We also include the interaction term between the Amihud measure and our mispricing measure to examine whether the illiquidity premium varies with mispricing. We follow Lou and Shu (2017) and include the following control variables. Ret[−12, −2] is the cumulative stock return from month $t-12$ to $t-2$. Ret[−1] is the stock return in month $t-1$. ME is the firm's market capitalization at the end of the previous year, measured in millions of dollars. B/M is the book-to-market ratio calculated as a firm's book value of equity divided by the firm's market capitalization. Both the Amihud measure and B/M are winsorized at the 1st and 99th percentiles to minimize the impact of outliers. We estimate regression Equation (3) month-by-month by following the Fama and MacBeth (1973) approach. We follow Lou and Shu (2017) and calculate t statistics using Newey–West standard errors with six lags.

Table 5 reports the results. We estimate four regression models. Model (1) is a univariate regression, where the Amihud illiquidity measure is the only regressor. We find a positive and significant coefficient on the Amihud measure. This finding is consistent with Amihud (2002), Lou and Shu (2017), as well as our earlier portfolio results. Models (2)–(4) control for our mispricing measure, an interaction term between the Amihud measure and the mispricing measure, and several stock characteristics including size, book-to-market and past returns. Regardless of which model we look at, we continue to find a significant and positive relation between the Amihud measure and stock returns. In particular, the coefficient on the Amihud measure remains statistically and economically significant after we control for the mispricing measure. In fact, the coefficient on the Amihud measure changes very little after controlling for the mispricing measure. This finding is inconsistent with the contention that the positive

TABLE 5 Illiquidity and stock returns—cross-sectional regressions.

This table reports the results from Fama–MacBeth cross-sectional regressions. We obtain stock data from the CRSP and accounting data from Compustat. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2018. The dependent variable is the monthly benchmark adjusted returns at month t, based on the Fama and French three-factor model. The independent variables include the natural logs of the Amihud measure, which is defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in month $t-2$. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. Ret[−12, −2] is the cumulative stock return from month $t-12$ to $t-2$, and Ret[−1] is the stock return in month $t-1$. ME is the firm's market capitalization at the end of the previous year, measured in millions of dollars. B/M is the book-to-market ratio calculated as a firm's book value of equity divided by the firm's market capitalization. The Amihud measure and B/M are winsorized at the 1st and 99th percentiles in each cross-section. All t statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	(1)	(2)	(3)	(4)
Intercept	0.0017	−0.0164	−0.0005	0.0005
	(2.87)	(−4.90)	(−0.14)	(0.15)
ln(Amihud)	0.0004	0.0016	0.0014	0.0022
	(3.00)	(5.29)	(4.72)	(5.94)
Mispricing Rank			−0.0217	−0.0254
			(−10.33)	(−10.09)
ln(Amihud) × Mispricing				−0.0015
				(−3.00)
Ret[−12, −2]		0.0057	0.0037	0.0037
		(4.12)	(2.61)	(2.64)
Ret[−1]		−0.0476	−0.0489	−0.0490
		(−10.91)	(−11.22)	(−11.20)
ln(ME)		0.0016	0.0011	0.0012
		(5.12)	(3.74)	(4.05)
B/M		0.0013	0.0016	0.0015
		(2.46)	(2.94)	(2.85)
Adjusted R^2	0.0032	0.0236	0.0259	0.0265

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

Amihud measure–return relation is driven by mispricing. In addition, we find a negative and significant coefficient on the interaction term between the Amihud measure and the mispricing measure. Recall that our mispricing measure is constructed so that it is positively correlated with overpricing. Therefore, the above result suggests that the positive Amihud–return relation is weaker among overpriced stocks, consistent with our double-sort results reported in Table 4. Finally, we find a negative and highly significant coefficient on our mispricing measure, confirming that overpriced stocks earn significantly lower returns. Overall, our regression results are consistent with those of the portfolio analysis.

3.4 | The A_C measure

Lou and Shu (2017) argue that the pricing of the Amihud measure is driven by the trading volume component, not by the ratio of absolute return to trading volume. Specifically, they construct a "constant" version of Amihud measure, that is, the A_C measure, where the absolute return component is set to 1. They show that the A_C measure is significantly and positively related to stock returns, whereas the residual from regressing the Amihud measure on the A_C measure is negatively related to returns.

To check whether Lou and Shu's (2017) finding holds in our sample, we construct the A_C measure and the residual Amihud measure as in Lou and Shu. Specifically, the A_C measure is defined as

$$\mathrm{A\_C}_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{1}{\mathrm{Dvol}_{id}}, \tag{4}$$

which is identical to the definition of the Amihud measure in Equation (1) except that the absolute return, $|r_{id}|$, is replaced with one. In addition, we construct a residual Amihud measure by orthogonalizing the Amihud measure with respect to the A_C measure, as in Lou and Shu (2017). Specifically, we estimate a cross-sectional regression of the logarithm of the Amihud measure on the logarithm of the A_C measure each month and obtain the regression residuals as the residual Amihud measure.

We sort sample stocks into quintiles by the A_C measure or the residual Amihud measure and examine the return difference between the highest- and lowest-illiquidity quintiles. Panel A of Table 6 reports the results for the A_C measure. Similar to the Amihud measure, we find that stocks in the highest A_C quintile significantly outperform those in the lowest A_C quintile. The outperformance is 0.36% (0.37%) per month for equal- (value-) weighted raw returns with t statistics of 2.75 (2.67). These numbers are similar to the corresponding numbers for the Amihud measure (reported in Table 3). The four-factor alpha results reveal a slightly larger illiquidity premium for the A_C measure than for the Amihud measure. For example, Table 6 reports an equal-weighted four-factor alpha of 0.31% per month (t statistic = 3.16) based on the A_C measure, compared with 0.26% (t statistic = 2.75) for the Amihud measure reported in Table 3. Similarly, the value-weighted four-factor alpha for the illiquidity premium is 0.21% per month and highly significant with a t statistic of 2.71 in Table 6, compared with 0.17% (t statistic = 2.10) for the Amihud measure. Panel B presents the results for the residual Amihud measure. Consistent with Lou and Shu (2017), we find no evidence that the residual Amihud measure is positively related to the cross-section of stock returns. In fact, there is some evidence of a negative relation between the residual Amihud measure and the stock returns.

We also examine the pricing of the A_C measure and the residual Amihud measure by using cross-sectional regressions. Specifically, we estimate regressions that are similar to Equation (3) except that we replace the Amihud measure with the A_C measure or the residual Amihud measure. Table 7 reports the regression results. We find a significant and positive

TABLE 6 A_C measure, the residual Amihud measure and stock returns—portfolios.

This table reports the raw returns and four-factor alphas of portfolios formed by sorting stocks on the constant version of Amihud measure (A_C) and the residual Amihud measure. We obtain stock data from the CRSP and accounting data from Compustat. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2018. A_C is defined as the daily ratio of 1 to dollar trading volume, averaged across all trading days in month $t-2$. We estimate a cross-sectional regression of the Amihud measure on the A_C measure each month and obtain the regression residuals as the residual Amihud measure. We construct equal-weighted as well as value-weighted portfolios and hold the portfolios for 1 month. We compute returns for each illiquidity-sorted portfolio as well as the return difference between the most illiquid and most liquid portfolios. All t statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Low	2	3	4	High	High–low
Panel A: The A_C measure						
			Equal weight			
Raw return	0.94	1.04	1.14	1.22	1.30	0.36
	(4.63)	(4.76)	(4.98)	(5.33)	(5.76)	(2.75)
α_4	−0.03	−0.01	0.04	0.12	0.29	0.31
	(−0.58)	(−0.18)	(0.82)	(2.46)	(3.42)	(3.16)
			Value weight			
Raw return	0.87	1.03	1.12	1.12	1.24	0.37
	(5.03)	(5.49)	(5.67)	(5.60)	(5.90)	(2.67)
α_4	0.01	0.04	0.08	0.08	0.22	0.21
	(0.54)	(0.88)	(1.69)	(1.58)	(2.85)	(2.71)
Panel B: The residual Amihud measure						
			Equal weight			
Raw return	1.13	1.20	1.23	1.15	0.93	−0.20
	(6.66)	(6.40)	(5.73)	(4.72)	(3.19)	(−1.10)
α_4	0.22	0.19	0.15	0.04	−0.18	−0.40
	(3.12)	(3.82)	(3.02)	(0.75)	(−2.53)	(−3.44)
			Value weight			
Raw return	0.82	0.97	0.92	0.96	0.74	−0.08
	(5.84)	(5.64)	(4.43)	(3.92)	(2.33)	(−0.33)
α_4	0.01	0.08	0.01	−0.03	−0.24	−0.25
	(0.18)	(2.05)	(0.20)	(−0.29)	(−1.98)	(−1.54)

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

TABLE 7 A_C measure, the residual Amihud measure and stock returns—regressions.

This table reports the results from Fama–MacBeth cross-section regressions using the constant version of Amihud measure (A_C). We obtain stock data from the CRSP and accounting data from Compustat. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2018. The dependent variable is the monthly benchmark adjusted returns of month t, based on the Fama and French three-factor model. The independent variables include the natural logs of A_C and the residual Amihud measure. A_C is defined as the daily ratio of 1 to dollar trading volume, averaged across all trading days in month $t-2$. We estimate a cross-sectional regression of the Amihud measure on the A_C measure each month and obtain the regression residuals as the residual Amihud measure. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. Ret [−12, −2] is the cumulative stock return from month $t-12$ to $t-2$, and Ret[−1] is the stock return in month $t-1$. ME is the firm's market capitalization at the end of the previous year, measured in millions of dollars. B/M is the book-to-market ratio calculated as a firm's book value of equity divided by the firm's market capitalization. The A_C measure and B/M are winsorized at the 1st and 99th percentiles in each cross-section. All t statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	(1)	(2)	(3)	(4)
Panel A: A_C				
Intercept	−0.0005	−0.0305	−0.0131	−0.0147
	(−0.98)	(−6.15)	(−2.63)	(−2.93)
ln(A_C)	0.0006	0.0020	0.0017	0.0024
	(3.74)	(6.35)	(5.55)	(6.29)
Mispricing Rank			−0.0206	−0.0187
			(−10.01)	(−7.04)
ln(A_C) × Mispricing				−0.0012
				(−2.26)
Ret[−12, −2]		0.0059	0.0040	0.0040
		(4.32)	(2.84)	(2.87)
Ret[−1]		−0.0478	−0.0490	−0.0490
		(−10.99)	(−11.27)	(−11.26)
ln(ME)		0.0021	0.0016	0.0016
		(6.14)	(4.70)	(4.92)
B/M		0.0009	0.0012	0.0012
		(1.83)	(2.39)	(2.32)
Adjusted R^2	0.0037	0.0252	0.0274	0.0280
Panel B: Residual Amihud				
Intercept	0.0003	0.0059	0.0179	0.0179
	(0.83)	(2.74)	(7.35)	(7.36)

TABLE 7 (Continued)

	(1)	(2)	(3)	(4)
Residual Amihud	−0.0030	−0.0039	−0.0033	0.0016
	(−4.58)	(−6.31)	(−5.51)	(1.33)
Mispricing rank			−0.0210	−0.0207
			(−10.54)	(−10.41)
Residual Amihud × Mispricing				−0.0097
				(−4.07)
Ret[−12, −2]		0.0044	0.0027	0.0025
		(3.20)	(1.90)	(1.79)
Ret[−1]		−0.0486	−0.0497	−0.0499
		(−11.21)	(−11.45)	(−11.48)
ln(ME)		−0.0006	−0.0007	−0.0007
		(−3.44)	(−4.11)	(−4.08)
B/*M*		0.0010	0.0013	0.0012
		(1.94)	(2.51)	(2.36)
Adjusted R^2	0.0038	0.0241	0.0262	0.0270

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

relation between the A_C measure and stock returns. Comparing with the results in Table 5 for the Amihud measure, we find that the *t* statistics are slightly higher for the A_C measure. We also find that the positive A_C measure–return relation is weaker among overpriced stocks, consistent with the limit-to-arbitrage argument. Panel B reports the results for the residual Amihud measure. Consistent with Lou and Shu (2017), we find a negative and significant relation between this measure and future stock returns.[12]

3.5 | Illiquidity measures and mispricing

Lou and Shu's (2017) finding that the trading volume component is driving the positive Amihud–return relation is not inconsistent with illiquidity premium because trading volume has been widely used and interpreted as a liquidity measure as well. Lou and Shu (2017), however, present additional evidence implying that the positive Amihud–return relation is caused by mispricing, not by compensation for illiquidity. Specifically, Lou and Shu (2017) show that the volume premium is significantly larger during high-sentiment periods and is primarily driven by the

[12]The coefficient on the residual Amihud measure is negative and statistically significant in the first three regression models in Panel B of Table 7. The coefficient turns positive in Model (4), but this model also includes an interaction term between the mispricing rank and the residual Amihud measure and the coefficient on this term is negative and highly significant. Combining these two effects leads to an overall negative relation between the residual Amihud measure and stock returns.

short side. They also show that the volume premium is concentrated during the earnings announcement period and is nonexistent during the nonannouncement window.

The evidence presented by Lou and Shu (2017) is informative, but indirect. They examine turnover, not trading volume or the Amihud measure directly. Moreover, they do not link the above liquidity measures directly to a mispricing measure. In this section, we perform a direct test of the hypothesis that the positive Amihud measure (or A_C measure)–return relation reflects mispricing rather than compensation for illiquidity by linking these illiquidity measures directly to our mispricing measure. If Lou and Shu's (2017) interpretation is correct, then we would expect stocks with a high Amihud measure or a high A_C measure to be relatively undervalued and therefore earn higher subsequent returns. The limit-to-arbitrage argument, on the other hand, predicts the opposite. Specifically, stocks with higher A_C or Amihud measures are more susceptible to mispricing due to greater limits-to-arbitrage. Because of arbitrage asymmetry, that is, shorting is more costly than buying, illiquid stocks will be more likely to be overvalued than undervalued. Therefore, we should find stocks with a high Amihud measure or a high A_C measure to be relatively overvalued.

We test the above opposing predictions by sorting all sample stocks into quintiles based on the A_C measure or the Amihud measure. We then calculate the average mispricing rank across all stocks in each illiquidity quintile. We also compute the difference in the mispricing measure between the highest-illiquidity quintile and the lowest-illiquidity quintile. Table 8 presents the result. We find that stocks in the highest-illiquidity quintile are more overvalued than stocks in the lowest-

TABLE 8 Illiquidity and overpricing percentile ranks.

This table reports the average overpricing percentile rank of portfolios formed by sorting stocks on the Amihud measure or the A_C measure. We obtain stock data from the CRSP. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than \$5. Our sample period is from August 1963 to December 2018. The Amihud measure is defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in a month. A_C is defined as the daily ratio of 1 to dollar trading volume, averaged across all trading days in a month. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. We sort all sample stocks into quintiles based on the Amihud measure or the A_C measure. The *t* statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Overpricing rank	
	Sort on Amihud	**Sort on A_C**
1—Lowest illiquidity	48.51	48.82
2	50.79	51.06
3	51.40	51.46
4	51.45	51.08
5—Highest illiquidity	51.31	50.85
High–low	2.80	2.02
	(6.54)	(4.72)

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

illiquidity quintile. For example, the average overpricing percentile rank is 51.31 for stocks in the highest Amihud quintile, and 48.51 for stocks in the lowest Amihud quintile. The difference of 2.80 is statistically significant with a *t* statistic of 6.54. The results for the A_C measure are qualitatively similar. Stocks in the highest A_C quintile exhibit significantly higher overpricing percentile rank than the lowest A_C quintile (50.85 vs. 48.82).[13] These results suggest that stocks with higher Amihud and A_C measures are more overvalued. This finding is inconsistent with the contention that such stocks earn higher returns because they are relatively undervalued, but is exactly what the arbitrage asymmetry argument predicts. That is, because shorting is more difficult and more costly than buying, illiquid stocks will tend to be more overpriced rather than underpriced.

3.6 | Three components of the Amihud (2002) measure

Amihud and Noh (2021) show that the Amihud (2002) measure can be decomposed into three terms—the absolute return, the inverse dollar trading volume and the covariance between absolute return and the inverse dollar volume. They contend that Lou and Shu (2017) overlooked the covariance term, and that this term affects stock returns significantly, both in the cross-section and in the time series. To find out which component(s) of the Amihud measure drive our main results, we repeat the main analyses for each component separately.

We conduct Fama–MacBeth cross-section regressions using each component to examine whether there are asymmetric illiquidity effects between underpriced stocks and overpriced stocks. More specifically, we regress the Fama and French three-factor adjusted stock returns on the natural logs of the component of Amihud measures, the mispricing measure, the interaction term between the component and the mispricing measure, and control variables. Regression results for the three components are presented in Table 9. As we can see from the table, the interaction term between the illiquidity component and the mispricing measure is always negative, no matter which component we examine. Moreover, the coefficient is statistically significant for both the absolute return component (with *t* statistics = −4.86) and the inverse dollar volume (with *t* statistics = −2.26). The results from the regression analyses suggest that all three components will generate the asymmetric illiquidity premium between overpriced stocks and underpriced stocks. That is, no matter which component of the Amihud measure we use, we should continue to find the illiquidity premium to be higher among underpriced stocks than among overpriced stocks.

4 | ADDITIONAL ANALYSES

4.1 | Quarterly rebalanced portfolios

In this paper, we have shown that excluding the most mispriced stocks will lead to a more reliable and more significant illiquidity premium. However, trading the liquidity factor is notoriously expensive in reality. According to Chen and Velikov (2023), the Amihud liquidity

[13]We acknowledge that these differences are economically small (they are small in part because the mispricing measure is averaged across 11 different anomalies and then across hundreds of stocks in each illiquidity portfolio). However, they are of the *opposite* sign to the prediction that stocks with high Amihud or A_C measures are undervalued, and therefore strongly reject the hypothesis that the positive Amihud–return relation is driven by mispricing.

TABLE 9 Three components of Amihud measure—regressions analysis.

This table reports the results from Fama–MacBeth cross-section regressions using the components of Amihud measures. We obtain stock data from the CRSP and accounting data from Compustat. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than \$5. Our sample period is from August 1963 to December 2018. The dependent variable is the monthly benchmark adjusted returns of month t, based on the Fama and French three-factor model. The independent variables include the natural logs of the components of Amihud measures. ln(Absolute) is the natural log of the average of absolute return across all trading days in month $t-2$. ln(A_C) is defined as the natural log of the average of the daily ratio of 1 to dollar trading volume across all trading days in month $t-2$. ln(Cov) is defined as the natural log of the covariance between absolute return and A_C measure in month $t-2$. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. Ret[−12, −2] is the cumulative stock return from month $t-12$ to $t-2$, and Ret[−1] is the stock return in month $t-1$. ME is the firm's market capitalization at the end of the previous year, measured in millions of dollars. B/M is the book-to-market ratio calculated as a firm's book value of equity divided by the firm's market capitalization. B/M are winsorized at the 1st and 99th percentiles in each cross-section. All t statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	(1)	(2)	(3)
Intercept	0.0250	−0.0147	0.0155
	(3.99)	(−2.93)	(3.98)
ln(Absolute)	0.0015		
	(1.12)		
ln(A_C)		0.0024	
		(6.29)	
ln(Cov)			0.0009
			(2.15)
Mispricing Rank	−0.0701	−0.0187	−0.0251
	(−6.04)	(−7.04)	(−4.93)
Mispricing Rank × ln(Absolute)	−0.0124		
	(−4.86)		
Mispricing Rank × ln(A_C)		−0.0012	
		(−2.26)	
Mispricing Rank × ln(Cov)			−0.0008
			(−1.03)
Ret[−12, −2]	0.0027	0.0040	−0.0001
	(1.90)	(2.87)	(−0.06)
Ret[−1]	−0.0504	−0.0490	−0.0633
	(−11.57)	(−11.26)	(−9.43)

TABLE 9 (Continued)

	(1)	(2)	(3)
ln(ME)	−0.0008	0.0016	0.0001
	(−4.94)	(4.92)	(0.26)
B/*M*	0.0009	0.0012	0.0004
	(1.76)	(2.32)	(0.58)
Adjusted R^2	0.0279	0.0280	0.0369

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

factor is one of the most expensive anomaly factors, due to the high turnover ratio (over 15% per month) of the portfolio. But Chen and Velikov (2023) also show that the liquidity factor still has positive abnormal returns after trading costs for monthly-rebalanced equal-weighted portfolios. They also suggest that trading costs can be mitigated by forming value-weighted portfolios or optimizing buy/hold spread.[14]

To investigate whether the Amihud factor is still profitable with a lower rebalancing frequency and thus lower costs, we construct a quarterly rebalanced illiquidity portfolio.[15] More specifically, we sort stocks into quintiles at the end of each quarter based on the Amihud illiquidity ratio of last month. We form both equal- and value-weighted long-short portfolios by holding stocks in quintile 5 and short-selling stocks in quintile 1, and we hold the portfolios for 3 months. Table 10 reports raw returns and four-factor alphas of the portfolios. Looking at the equal-weighted returns in Panel A, we can see that the overall illiquidity premium for all stocks is still positive and statistically significant (0.36% per month with t statistic = 2.69). More importantly, the illiquidity premium becomes even more pronounced at 0.42% per month (t statistic = 3.27) when we exclude the most overpriced stocks from the sample. When we control for the risk factors, the four-factor alpha of the same portfolio is around 0.34% per month (t statistic = 3.91). When we examine the value-weighted portfolios, the results are qualitatively the same. Overall, the results in Table 10 suggest that the illiquidity premium is still economically large and statistically significant when the portfolio is rebalanced at the quarterly frequency, and investors can profit from this factor with a much lower cost compared with the conventional illiquidity portfolio.

4.2 | Investor sentiment

The central prediction of the limit-to-arbitrage argument presented earlier is that overpricing induces a negative illiquidity–return relation, which reduces the observed illiquidity premium. We perform tests of this prediction in Tables 4 and 5 by comparing the observed illiquidity premium across overpriced and underpriced stocks. We find that, consistent with the limit-to-arbitrage argument, the illiquidity premium is significantly higher among underpriced stocks than among overpriced stocks.

[14]He et al. (2023) also provide detailed discussions on transaction costs.

[15]Cong et al. (2023) suggest using quarterly or annually rebalanced portfolios to reduce trading costs for anomalies.

TABLE 10 Illiquidity, mispricing and the cross-section of stock returns—quarterly rebalancing.

This table reports the raw returns and four-factor alphas of portfolios formed at the end of each quarter by sorting stocks independently on the Amihud measure and our mispricing measure. Our sample period is from August 1963 to December 2018. The Amihud measure is defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in a month. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies. We construct equal-weighted as well as value-weighted portfolios at the end of each quarter and hold the portfolios for 3 months. We obtain Fama and French (1993) three factors and the momentum factor from Kenneth French's website. The *t* statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Lowest illiquidity	2	3	4	Highest illiquidity	High–low
Panel A: Equal-weighted returns						
Raw return						
Q1 (overpriced)	0.47	0.57	0.60	0.68	0.81	0.34
	(1.81)	(2.15)	(2.20)	(2.53)	(2.99)	(1.98)
Q2	0.82	0.99	1.10	1.15	1.25	0.43
	(3.92)	(4.40)	(4.59)	(4.85)	(5.08)	(3.03)
Q3	1.01	1.17	1.23	1.31	1.39	0.38
	(5.20)	(5.44)	(5.36)	(5.75)	(5.90)	(2.70)
Q4	1.08	1.26	1.40	1.31	1.48	0.41
	(5.83)	(6.33)	(6.38)	(5.76)	(6.65)	(2.95)
Q5 (underpriced)	1.17	1.36	1.39	1.58	1.77	0.59
	(6.83)	(6.68)	(6.55)	(6.98)	(7.86)	(4.32)
Q5–Q1	0.70	0.79	0.79	0.90	0.96	0.26
	(4.87)	(6.61)	(6.27)	(7.58)	(10.40)	(1.82)
Q2–Q5	1.04	1.19	1.27	1.33	1.46	0.42
	(5.68)	(5.75)	(5.73)	(5.86)	(6.41)	(3.27)
Q2–Q4	0.98	1.14	1.23	1.26	1.37	0.39
	(5.12)	(5.44)	(5.44)	(5.50)	(5.93)	(2.94)
All stocks	0.97	1.06	1.12	1.18	1.32	0.36
	(5.07)	(4.94)	(4.87)	(5.01)	(5.60)	(2.69)
Four-factor alpha						
Q1 (overpriced)	−0.34	−0.37	−0.37	−0.36	−0.19	0.15
	(−3.36)	(−4.48)	(−4.21)	(−4.72)	(−1.68)	(1.08)
Q2	−0.12	−0.07	0.01	0.05	0.20	0.33
	(−2.03)	(−1.05)	(0.16)	(0.81)	(2.16)	(3.06)
Q3	0.06	0.14	0.11	0.20	0.36	0.30
	(0.96)	(2.10)	(1.80)	(3.15)	(3.91)	(2.85)

TABLE 10 (Continued)

	Lowest illiquidity	2	3	4	Highest illiquidity	High–low
Q4	0.10	0.19	0.26	0.17	0.47	0.37
	(1.89)	(2.77)	(3.96)	(2.64)	(4.10)	(3.07)
Q5 (underpriced)	0.23	0.30	0.31	0.46	0.74	0.51
	(4.14)	(4.67)	(3.87)	(5.38)	(8.13)	(5.14)
Q5–Q1	0.58	0.67	0.68	0.82	0.94	0.36
	(5.19)	(7.02)	(6.73)	(7.84)	(10.15)	(2.79)
Q2–Q5	0.09	0.13	0.16	0.21	0.43	0.34
	(2.06)	(2.60)	(3.09)	(3.88)	(5.34)	(3.91)
Q2–Q4	0.02	0.09	0.12	0.14	0.34	0.31
	(0.50)	(1.60)	(2.26)	(2.66)	(4.01)	(3.34)
All stocks	0.03	0.03	0.05	0.08	0.30	0.26
	(0.78)	(0.65)	(0.88)	(1.50)	(3.55)	(2.90)
Panel B: Value-weighted returns						
Raw return						
Q1 (overpriced)	0.44	0.61	0.67	0.68	0.75	0.31
	(1.74)	(2.51)	(2.72)	(2.75)	(2.94)	(1.79)
Q2	0.73	0.91	1.07	1.03	1.17	0.44
	(3.60)	(4.43)	(4.86)	(4.62)	(5.00)	(2.89)
Q3	0.82	1.06	1.16	1.22	1.32	0.50
	(4.56)	(5.30)	(5.52)	(5.93)	(5.62)	(3.06)
Q4	0.94	1.20	1.29	1.24	1.36	0.42
	(5.52)	(6.55)	(6.40)	(5.97)	(6.77)	(2.75)
Q5 (underpriced)	1.00	1.20	1.24	1.47	1.67	0.67
	(6.15)	(6.55)	(6.50)	(6.99)	(7.74)	(4.21)
Q5–Q1	0.56	0.59	0.56	0.79	0.92	0.36
	(3.62)	(5.04)	(4.86)	(6.61)	(9.06)	(2.24)
Q2–Q5	0.91	1.09	1.19	1.23	1.37	0.46
	(5.46)	(5.79)	(5.92)	(5.95)	(6.39)	(3.21)
Q2–Q4	0.85	1.06	1.17	1.16	1.28	0.43
	(4.86)	(5.50)	(5.68)	(5.58)	(5.90)	(2.98)
All stocks	0.87	1.01	1.09	1.11	1.25	0.37
	(5.11)	(5.20)	(5.26)	(5.23)	(5.63)	(2.58)
Four-factor alpha						
Q1 (overpriced)	−0.37	−0.32	−0.32	−0.36	−0.27	0.10

(Continues)

TABLE 10 (Continued)

	Lowest illiquidity	2	3	4	Highest illiquidity	High–low
	(−3.74)	(−3.67)	(−4.39)	(−5.06)	(−2.59)	(0.77)
Q2	−0.20	−0.09	0.00	−0.05	0.11	0.31
	(−3.29)	(−1.46)	(0.07)	(−0.63)	(1.17)	(2.99)
Q3	−0.07	0.05	0.08	0.14	0.27	0.34
	(−1.37)	(0.83)	(1.30)	(2.39)	(2.44)	(2.75)
Q4	0.10	0.17	0.18	0.12	0.30	0.21
	(1.89)	(2.71)	(2.77)	(1.97)	(3.40)	(2.15)
Q5 (underpriced)	0.15	0.19	0.18	0.38	0.62	0.47
	(3.70)	(3.13)	(2.75)	(5.13)	(6.90)	(5.01)
Q5–Q1	0.52	0.51	0.50	0.74	0.89	0.37
	(4.29)	(5.03)	(5.12)	(7.04)	(8.36)	(2.53)
Q2–Q5	0.05	0.08	0.11	0.14	0.32	0.27
	(3.16)	(1.64)	(2.33)	(2.85)	(4.26)	(3.56)
Q2–Q4	−0.02	0.05	0.09	0.07	0.22	0.24
	(−0.81)	(0.89)	(1.74)	(1.42)	(2.82)	(2.92)
All stocks	0.02	0.01	0.03	0.03	0.20	0.18
	(1.41)	(0.29)	(0.68)	(0.77)	(2.66)	(2.41)

In this section, we test this prediction by using a time-series measure of overpricing. Specifically, if overpricing reduces the observed illiquidity premium, then we should find a lower illiquidity premium during periods when overpricing is more prevalent. We use the investor sentiment measure of Baker and Wurgler (2006) to gauge the extent of market-wide mispricing over time. We follow Stambaugh et al. (2012) and divide our sample period into high- and low-sentiment periods based on the median sentiment value. We then re-examine the illiquidity premium separately for high- and low-investment periods. To the extent that overpricing is more likely and more severe during high-sentiment periods, we should find significantly lower illiquidity premium during high-sentiment periods.

We report the results in Table 11. Panel A reports the equal-weighted results. We find that, during low-sentiment periods, the most illiquid stocks earn an average return of 1.46% per month, while the least illiquid stocks earn an average return of 0.93%. The illiquidity premium of 0.53% per month is economically large and statistically significant with a t statistic of 2.55. In comparison, the illiquidity premium is just 0.18% per month during high-sentiment periods and is statistically indistinguishable from zero. This result lends support to the limit-to-arbitrage argument.[16]

[16]Lou and Shu (2017) also perform an analysis of investor sentiment and find that the turnover premium is higher during high-sentiment periods. Their finding appears to be opposite of ours, but there are important differences between their analysis and ours. For example, Lou and Shu (2017) examine turnover, while we focus directly on the Amihud measure.

TABLE 11 Investor sentiment and illiquidity premium.

This table reports the raw returns and four-factor alphas of portfolios formed by sorting stocks independently on the Amihud measure and our mispricing measure following the high- and low-sentiment periods. We obtain stock data from the CRSP. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2014. The Amihud measure is defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in a month. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. We follow Stambaugh et al. (2012) and divide our sample period into high- and low-sentiment periods based on the median sentiment value. We construct equal-weighted as well as value-weighted portfolios. We report results for the two extreme illiquidity quintiles. We obtain Fama and French (1993) three factors and the momentum factor from Kenneth French's website. The t statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Low sentiment			**High sentiment**		
	Low illiquidity	**High illiquidity**	**High–low**	**Low illiquidity**	**High illiquidity**	**High–low**
Panel A: Equal-weighted returns						
Raw return						
Most Overpriced	0.59	0.95	0.36	0.30	0.50	0.20
	(1.57)	(2.35)	(1.47)	(0.79)	(1.28)	(0.74)
Next 20% (Q2)	0.86	1.47	0.60	0.84	0.96	0.12
	(2.56)	(3.80)	(2.52)	(2.70)	(2.69)	(0.52)
Next 20% (Q3)	0.95	1.45	0.50	1.11	1.30	0.19
	(3.00)	(3.99)	(2.51)	(4.09)	(3.57)	(0.86)
Next 20% (Q4)	0.98	1.58	0.59	1.23	1.58	0.36
	(3.35)	(4.44)	(2.79)	(4.57)	(4.52)	(1.60)
Most Underpriced	1.09	1.94	0.85	1.32	1.86	0.54
	(3.87)	(5.30)	(3.74)	(5.24)	(5.57)	(2.49)
Q5–Q1	0.50	0.99	0.49	1.02	1.36	0.34
	(2.54)	(8.40)	(2.52)	(4.79)	(10.41)	(1.52)
All stocks	0.93	1.46	0.53	1.03	1.22	0.18
	(3.08)	(3.92)	(2.55)	(3.68)	(3.44)	(0.87)
Four-factor alpha						
Most Overpriced	−0.28	−0.16	0.12	−0.57	−0.53	0.04
	(−1.97)	(−1.01)	(0.62)	(−4.13)	(−2.85)	(0.20)
Next 20% (Q2)	−0.04	0.36	0.40	−0.17	−0.14	0.03
	(−0.47)	(2.64)	(2.33)	(−1.60)	(−0.85)	(0.16)

(Continues)

TABLE 11 (Continued)

	Low sentiment			High sentiment		
	Low illiquidity	High illiquidity	High–low	Low illiquidity	High illiquidity	High–low
Next 20% (Q3)	0.01	0.35	0.34	0.03	0.20	0.17
	(0.11)	(2.75)	(2.27)	(0.33)	(1.19)	(0.88)
Next 20% (Q4)	0.05	0.47	0.42	0.17	0.49	0.32
	(0.64)	(3.52)	(2.65)	(1.96)	(2.43)	(1.51)
Most Underpriced	0.15	0.81	0.66	0.28	0.77	0.49
	(1.86)	(6.05)	(4.40)	(3.41)	(5.35)	(2.99)
Q5–Q1	0.43	0.97	0.54	0.85	1.30	0.45
	(2.69)	(7.93)	(3.10)	(5.15)	(10.39)	(2.30)
All stocks	0.01	0.35	0.35	0.01	0.13	0.12
	(0.13)	(2.88)	(2.48)	(0.23)	(0.86)	(0.71)
Panel B: Value-weighted returns						
Raw return						
Most Overpriced	0.57	0.84	0.27	0.34	0.51	0.16
	(1.54)	(2.14)	(1.04)	(0.91)	(1.39)	(0.62)
Next 20% (Q2)	0.59	1.35	0.76	0.77	0.99	0.22
	(1.78)	(3.59)	(2.96)	(2.71)	(2.94)	(0.87)
Next 20% (Q3)	0.70	1.30	0.59	1.04	1.26	0.23
	(2.52)	(3.65)	(2.79)	(4.16)	(3.60)	(0.91)
Next 20% (Q4)	0.88	1.42	0.54	1.01	1.50	0.48
	(3.32)	(3.98)	(2.23)	(3.58)	(4.83)	(1.92)
Most Underpriced	0.90	1.84	0.94	1.12	1.73	0.61
	(3.63)	(5.06)	(3.71)	(4.31)	(5.33)	(2.36)
Q5–Q1	0.33	1.00	0.67	0.78	1.23	0.45
	(1.46)	(6.71)	(2.90)	(3.47)	(8.48)	(1.94)
All stocks	0.78	1.34	0.56	0.96	1.18	0.21
	(3.01)	(3.71)	(2.58)	(3.60)	(3.61)	(0.88)
Four-factor alpha						
Most Overpriced	−0.17	−0.25	−0.08	−0.56	−0.54	0.02
	(−1.38)	(−1.67)	(−0.40)	(−4.08)	(−3.13)	(0.10)
Next 20% (Q2)	−0.23	0.27	0.50	−0.23	−0.11	0.12
	(−2.24)	(1.84)	(2.71)	(−2.43)	(−0.73)	(0.66)
Next 20% (Q3)	−0.09	0.22	0.31	0.06	0.13	0.07

TABLE 11 (Continued)

	Low sentiment			High sentiment		
	Low illiquidity	High illiquidity	High–low	Low illiquidity	High illiquidity	High–low
	(−1.21)	(1.49)	(1.89)	(0.81)	(0.74)	(0.36)
Next 20% (Q4)	0.08	0.32	0.24	0.10	0.36	0.26
	(1.23)	(2.04)	(1.37)	(1.28)	(2.58)	(1.65)
Most Underpriced	0.11	0.71	0.60	0.18	0.58	0.40
	(1.76)	(4.87)	(3.93)	(2.82)	(4.14)	(2.76)
Q5–Q1	0.28	0.95	0.68	0.74	1.12	0.38
	(1.81)	(6.22)	(3.18)	(4.22)	(7.51)	(1.87)
All stocks	−0.01	0.25	0.25	0.03	0.07	0.04
	(−0.37)	(2.06)	(2.10)	(1.39)	(0.50)	(0.29)

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

We further divide all sample stocks into mispricing quintiles and examine whether cross-sectional overpricing has an incremental effect on the observed illiquidity premium across high- and low-sentiment periods. During low-sentiment periods, we find that the illiquidity premium is 0.85% among the most underpriced stocks, and 0.36% among the most overpriced stocks. The difference in illiquidity premium between the most underpriced stocks and most overpriced stocks is 0.49% per month and statistically significant (t statistic = 2.52). During high-sentiment periods, we find that the illiquidity premium is 0.54% among the most underpriced stocks, and 0.20% among the most overpriced stocks. The difference in illiquidity premium between the most underpriced stocks and most overpriced stocks is economically meaningful at 0.34% per month but is statistically insignificant (t statistic = 1.52). Overall, our results indicate the impact of cross-sectional mispricing on the observed illiquidity premium is stronger during low-sentiment periods than during high-sentiment periods.

The results based on four-factor alphas are qualitatively similar. Specifically, we find that, during low-sentiment periods, the illiquidity premium of 0.35% per month is economically large and statistically significant with a t statistic of 2.48. In contrast, the illiquidity premium is just 0.12% per month during high-sentiment periods and is statistically indistinguishable from zero. During low-sentiment periods, the illiquidity premium is 0.12% among the most overpriced stocks, and 0.66% among the most underpriced stocks. The difference in illiquidity premium between the most underpriced stocks and most overpriced stocks is 0.54% per month and statistically significant (t statistic = 3.10). During high-sentiment periods, we find that the illiquidity premium to be 0.04% among the most overpriced stocks, and 0.49% among the most underpriced stocks. The difference of 0.45% per month is statistically significant (t statistic = 2.30).

The results in Panel B for value-weighted returns paint a similar picture. We find that the illiquidity premium is only present during low-sentiment periods (0.56%, t statistic = 2.58), and nonexistent during high-sentiment periods (0.21%, t statistic = 0.88). Furthermore, the illiquidity premium is higher among underpriced stocks than among overpriced stocks, and difference is larger during low-sentiment periods. Overall, our results for the investor sentiment analysis complement our previous cross-sectional result and suggest that the observed illiquidity premium is negatively related to the extent of overpricing.

4.3 | Market illiquidity

The overall market liquidity level could be an important factor affecting the illiquidity premium. When the overall market liquidity is low, the transaction costs and risks associated with illiquid assets tend to be higher. As a result, investors may demand higher returns for holding illiquid assets. In this section, we explore the impact of market liquidity on the cross-sectional illiquidity premium. We construct the time series of the overall market illiquidity measure by averaging the stock-level illiquidity ratios and divide our sample period into high- and low-illiquidity periods based on the median market illiquidity value. We then re-examine the illiquidity premium separately for high- and low-market-illiquidity periods.

We report the results in Table 12. Panel A presents the equal-weighted results. We find that, during high-market-illiquidity periods and for all stocks, the most illiquid stocks earn an average return of 1.82% per month, while the least illiquid stocks earn an average return of 1.21%. The illiquidity premium of 0.61% per month is economically large and statistically significant with a *t* statistic of 3.15. In comparison, the illiquidity premium is only 0.07% per month during low-market-illiquidity periods and is statistically indistinguishable from zero (t statistic = 0.37). When we examine the four-factor alphas of the portfolios, we continue to find that the illiquidity portfolio has a higher alpha during the high-market-illiquidity periods. The value-weighted results in Panel B paint a similar picture. Overall, we find strong evidence to support the hypothesis that investors demand a higher illiquidity premium when the overall market is illiquid.

4.4 | Market uncertainty

Investors might demand higher or lower returns for holding illiquidity assets when the market condition changes. To investigate this possibility, we obtain the macro uncertainty data of Jurado et al. (2015) from Professor Ludvigson′ website[17] and divide our sample period into high- and low-uncertainty periods based on the median macro uncertainty value. We then re-examine the illiquidity premium and the asymmetric effects between underpriced and overpriced stocks, separately for high- and low-market-uncertainty periods. We find that the raw returns of the illiquidity portfolio are higher during the high-uncertainty period, but the four-factor alpha of the portfolio is higher during the low-uncertainty period. Overall, we did not find consistent evidence regarding the impact of market uncertainty on the illiquidity premium, as the results depend on the benchmark model that we use to evaluate the portfolios. Detailed results of this analysis can be found in the Supporting Information Appendix.

[17]https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

TABLE 12 Market illiquidity and illiquidity premium.

This table reports the raw returns and four-factor alphas of portfolios formed by sorting stocks independently on the Amihud measure and our mispricing measure following the high and low-market-illiquidity periods. We obtain stock data from the CRSP. Our sample consists of NYSE, AMEX and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude stocks with a price lower than $5. Our sample period is from August 1963 to December 2018. The Amihud measure is defined as the daily ratio of absolute return to dollar trading volume, averaged across all trading days in a month. The mispricing measure is the arithmetic average of each stock's percentile ranks for the following 11 anomalies: Net Stock Issues, Composite Equity Issues, Accruals, Net Operating Assets, Asset Growth, Investment-to-Assets, Distress, O-score, Momentum, Gross Profitability Premium and Return on Assets. We assign percentile ranks based on the findings of prior literatures so that higher ranks correspond to overpricing and lower ranks correspond to underpricing. We calculate the market illiquidity measure as the equal-weighted average of the Amihud measure across NYSE and AMEX common stocks and divide our sample period into high- and low-illiquidity periods based on the median market illiquidity value. We construct equal-weighted as well as value-weighted portfolios. We report results for the two extreme illiquidity quintiles. We obtain Fama and French (1993) three factors and the momentum factor from Kenneth French's website. The *t* statistics (in parentheses) are calculated using Newey–West standard errors with six lags.

	Low market illiquidity			**High market illiquidity**		
	Low illiquidity	**High illiquidity**	**High–low**	**Low illiquidity**	**High illiquidity**	**High–low**
Panel A: Equal-weighted returns						
Raw return						
Most Overpriced	0.06	0.26	0.19	0.77	1.20	0.43
	(0.21)	(0.71)	(0.88)	(1.95)	(3.15)	(1.54)
Next 20% (Q2)	0.58	0.62	0.04	1.08	1.75	0.67
	(2.19)	(1.87)	(0.20)	(3.12)	(4.91)	(3.00)
Next 20% (Q3)	0.77	0.77	0.00	1.22	1.94	0.72
	(3.14)	(2.47)	(0.00)	(4.03)	(5.60)	(3.92)
Next 20% (Q4)	0.88	1.03	0.14	1.26	2.02	0.75
	(3.73)	(3.45)	(0.78)	(4.33)	(5.76)	(3.53)
Most Underpriced	0.87	1.33	0.45	1.48	2.27	0.79
	(3.87)	(4.33)	(2.14)	(5.33)	(6.72)	(4.11)
Q5–Q1	0.81	1.07	0.26	0.70	1.06	0.36
	(4.83)	(8.10)	(1.53)	(3.15)	(7.79)	(1.48)
All stocks	0.70	0.77	0.07	1.21	1.82	0.61
	(2.91)	(2.42)	(0.37)	(4.02)	(5.21)	(3.15)
Four-factor alpha						
Most Overpriced	−0.61	−0.35	0.26	−0.26	−0.20	0.06
	(−4.72)	(−2.11)	(1.30)	(−1.76)	(−1.35)	(0.28)
Next 20% (Q2)	−0.17	−0.02	0.15	−0.04	0.31	0.35
	(−2.08)	(−0.14)	(0.87)	(−0.39)	(2.50)	(2.27)

(Continues)

TABLE 12 (Continued)

	Low market illiquidity			High market illiquidity		
	Low illiquidity	High illiquidity	High–low	Low illiquidity	High illiquidity	High–low
Next 20% (Q3)	−0.02	0.12	0.14	0.05	0.54	0.49
	(−0.28)	(0.89)	(0.81)	(0.71)	(3.94)	(3.44)
Next 20% (Q4)	0.08	0.37	0.30	0.11	0.60	0.49
	(1.15)	(2.74)	(1.90)	(1.37)	(3.38)	(2.66)
Most Underpriced	0.07	0.66	0.59	0.34	0.85	0.51
	(1.24)	(4.80)	(3.64)	(4.14)	(6.44)	(3.91)
Q5–Q1	0.68	1.00	0.33	0.60	1.05	0.45
	(4.88)	(8.16)	(1.87)	(3.39)	(7.76)	(2.16)
All stocks	−0.07	0.13	0.20	0.09	0.40	0.31
	(−1.31)	(0.98)	(1.32)	(1.57)	(3.33)	(2.47)
Panel B: Value-weighted returns						
Raw returns						
Most Overpriced	0.18	0.35	0.17	0.71	0.99	0.28
	(0.58)	(1.02)	(0.77)	(1.85)	(2.73)	(1.01)
Next 20% (Q2)	0.55	0.66	0.11	0.80	1.60	0.80
	(2.33)	(2.14)	(0.54)	(2.41)	(4.61)	(3.13)
Next 20% (Q3)	0.85	0.70	−0.14	0.86	1.81	0.95
	(3.95)	(2.35)	(−0.76)	(3.11)	(5.33)	(4.46)
Next 20% (Q4)	0.90	0.97	0.07	0.96	1.81	0.85
	(4.10)	(3.52)	(0.38)	(3.41)	(5.26)	(3.42)
Most Underpriced	0.86	1.20	0.34	1.15	2.19	1.04
	(4.15)	(4.10)	(1.59)	(4.38)	(6.38)	(4.36)
Q5–Q1	0.68	0.85	0.17	0.44	1.19	0.76
	(3.27)	(6.10)	(0.81)	(1.96)	(7.85)	(3.01)
All stocks	0.77	0.79	0.01	0.96	1.66	0.70
	(3.71)	(2.65)	(0.06)	(3.49)	(4.90)	(3.15)
Four-factor alpha						
Most Overpriced	−0.51	−0.27	0.24	−0.20	−0.41	−0.21
	(−3.70)	(−1.84)	(1.29)	(−1.53)	(−2.86)	(−1.13)
Next 20% (Q2)	−0.22	0.01	0.23	−0.23	0.18	0.41
	(−2.86)	(0.10)	(1.42)	(−2.15)	(1.35)	(2.48)
Next 20% (Q3)	0.09	0.02	−0.07	−0.15	0.41	0.56
	(1.34)	(0.15)	(−0.43)	(−2.39)	(2.69)	(3.65)

TABLE 12 (Continued)

	Low market illiquidity			High market illiquidity		
	Low illiquidity	High illiquidity	High–low	Low illiquidity	High illiquidity	High–low
Next 20% (Q4)	0.14	0.29	0.16	0.01	0.39	0.38
	(2.12)	(2.22)	(1.05)	(0.22)	(2.63)	(2.31)
Most Underpriced	0.08	0.48	0.41	0.20	0.74	0.53
	(1.28)	(3.49)	(2.64)	(3.40)	(5.41)	(3.73)
Q5–Q1	0.59	0.75	0.17	0.40	1.15	0.74
	(3.40)	(5.65)	(0.80)	(2.44)	(7.24)	(3.30)
All stocks	0.02	0.11	0.10	0.01	0.24	0.23
	(1.01)	(1.00)	(0.85)	(0.51)	(2.12)	(2.02)

Abbreviations: AMEX, American Stock Exchange; CRSP, Center for Research in Security Prices; NASDAQ, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

4.5 | NYSE/AMEX stocks

In our main analyses, we include stocks from all three main exchanges, NYSE, AMEX and NASDAQ. We adjust the trading volume of NASDAQ stocks to make it comparable to that of NYSE and AMEX stocks. In this section, we exclude NASDAQ stocks from our sample and check whether our results are robust. Specifically, we rerun the analyses in Tables 4 and 5 for NYSE and AMEX stocks only.

In portfolio analysis, we use double sort to examine whether the illiquidity premium varies with the degree of mispricing. Overall, the results are similar to those in Table 4. We find that the observed illiquidity premium is significantly higher among underpriced stocks than among overpriced stocks. Excluding both Q1 and Q5 leads to an illiquidity premium of 0.32% per month (t statistic = 2.48), which is also higher than that for the full sample and is more reliably estimated. An examination of four-factor alphas or value-weighted portfolios reveals qualitatively similar results.

We also repeat the cross-sectional regression analysis in Table 5 for NYSE/AMEX stocks and present the results in the Supporting Information Appendix. As in Table 5, we estimate four regression models. Regardless of which model we look at, we continue to find a significant and positive relation between the Amihud measure and stock returns. In addition, we find a negative and significant coefficient on the interaction term between the Amihud measure and the mispricing measure. This result suggests that the positive Amihud–return relation is weaker among overpriced stocks, and is consistent with our double-sort results. Overall, our results are qualitatively unchanged when we exclude NASDAQ stocks from our sample. Detailed results can be found in the Supporting Information Appendix.

4.6 | Half Amihud measures

Brennan et al. (2013) and Lou and Shu (2017) construct half Amihud measures based only on positive or negative returns. The motivation for this analysis is that the illiquidity measured during up and down days may have a different impact on asset prices. In particular, one might argue that illiquidity during down markets is more critical for investors and therefore they demand a greater illiquidity premium. In this section, we examine whether our main results are robust to these half Amihud measures. We follow Brennan et al. (2013) and Lou and Shu (2017) and construct the half Amihud measures as follows:

$$\mathrm{AP}_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{\max[r_{id}, 0]}{\mathrm{Dvol}_{id}}, \tag{5}$$

$$\mathrm{AN}_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{-\min[r_{id}, 0]}{\mathrm{Dvol}_{id}}. \tag{6}$$

When we construct the above half Amihud measures, we require a minimum of five daily observations during a month.

We conduct the double-sort portfolio analysis for half Amihud measures. Consistent with our results for the full Amihud measure, we find that the observed illiquidity premium is significantly higher among underpriced stocks than among overpriced stocks. When we use the AP measure, the highest-illiquidity quintile outperforms the lowest illiquidity quintile by 0.60% per month (t statistic = 4.24) among the most underpriced stock quintile, but by only 0.36% per month (t statistic = 2.24) among the most overpriced stocks. The difference in illiquidity premium between the most underpriced stocks and most overpriced stocks is 0.24% per month, and statistically significant at the 10% level with a t statistic of 1.73. Excluding both the most overpriced and most underpriced stocks leads to an illiquidity premium of 0.35% per month (t statistic = 2.73). Examining four-factor alphas does not change the qualitative results. When we use the AN measure for portfolio sorts, we obtain similar results. Overall, we find that our previous portfolio results continue to hold for both half Amihud measures.

To examine which of the half Amihud measures is more important, we follow Brennan et al. (2013) and Lou and Shu (2017) and use a multiple regression framework. Specifically, we estimate a multiple regression similar to regression Equation (3) by including both AP and AN (and their interactions with the mispricing measure). We find results similar to the full Amihud measure. That is, we find a significant positive relation between the half Amihud measures and stock returns. Moreover, we find that this relation is less positive among overpriced stocks. That is, the coefficient on the interaction term between the half Amihud measures and the mispricing measure is negative. This result is again consistent with our previous results that the illiquidity premium is lower among overpriced stocks.

When we include both the AP and the AN measure in the regression, we find only the AN measure is significantly and positively related to the stock returns. The coefficient on the AP measure, after controlling for the AN measure, is actually negative, albeit statistically insignificant. This finding is consistent with Brennan et al. (2013) and Lou and Shu (2017) and suggests that the Amihud measure during down days is more strongly related to stock returns.

5 | CONCLUSIONS

Illiquid assets require a return premium. Illiquidity is also a limit-to-arbitrage, which induces a negative (positive) illiquidity–return relation among overpriced (underpriced) stocks. Arbitrage asymmetry implies an overall negative illiquidity–return relation, reducing the observed illiquidity premium. Prior studies that do not account for this effect tend to understate the magnitude of the illiquidity premium. Consistent with these predictions, we find that the illiquidity premium based on Amihud's (2002) measure is significantly higher among underpriced stocks than among overpriced stocks. Similarly, the illiquidity premium is significantly higher during low-sentiment periods than during high-sentiment periods. Excluding the most overpriced stocks or the most mispriced stocks leads to a higher and more reliably estimated illiquidity premium. Finally, we show that both the Amihud measure and the A_C measure are positively related to a composite mispricing measure based on well-documented anomalies, consistent with the predictions of arbitrage asymmetry while inconsistent with Lou and Shu's (2017) contention that the positive Amihud–return relation is due to mispricing. Overall, our findings suggest that it is important to account for the limits-to-arbitrage effect when examining the pricing of illiquidity measures.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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