Investor Sentiment and the Time Variation of the Illiquidity Premium

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Abstract

This paper examines the return premium associated with illiquidity through time. Prior research has documented that investors command a return premium for holding the most illiquid stocks. The idea behind the return premium is that investors demand higher returns as compensation for the risk of not being able to liquidate their position in a timely manner (see Amihud and Mendelson 1986). We find that the illiquidity premium has substantial variation across time. For instance, during the 25 years examined, the illiquidity premium is only significant in 11 of those years. In fact, the standard deviation of the illiquidity return premium is greater than the average return premium in some specifications. In additional tests, we find that during periods of low investor sentiment, the illiquidity premium is the highest, suggesting that sentiment might contribute to the observed time variation in the premium.

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Introduction

The relationship between liquidity and expected returns has been well documented. Brennan and Subrahmanyam (1996), Datar, Naik, and Radcliffe (1998), Liu (2006), and Han and Lesmond (2011) are examples of research that has shown that less liquid securities outperform more liquid securities. This illiquidity return premium stems from investors demanding a higher return for a security that is harder to liquidate and is both intuitive and empirically robust. Ibbotson et al. (2013) argue that returns from liquidity are unique and should be considered as an independent investment style similar to size, value, or momentum. This idea is not new. Pástor and Stambaugh (2003) create a liquidity risk factor that buys stocks with low liquidity and shorts stocks with high liquidity and show that this risk factor explains a substantial proportion of expected returns.

The 2008–2009 financial crisis has highlighted the importance of considering liquidity when forming a portfolio (see Lou and Sadka (2011)). For instance, illiquidity, estimated according to Amihud (2002), surged during the financial crisis and was higher in 2009 than in any of the previous 15 years. Brunnermeier and Pedersen (2009) document how liquidity is subject to “flight to quality” issues or can “dry up,” which can lead to liquidity spirals. Even before the crisis, Persaud (2003) suggested that there is a broad belief among practitioners and regulators that the principal concern about liquidity in financial markets is not the average level of liquidity, which has improved over time, but the variability and the uncertainty of liquidity. These findings highlight the importance of the time-varying aspect of liquidity and underlie the need to understand what factors influence changes in liquidity and how a time-varying illiquidity premium might impact both the performance and rebalancing of portfolios. The focus of this paper is not to argue that changes in liquidity are “better” than levels of liquidity but to highlight that the cyclical nature of the time variation of liquidity can be informative, despite low average levels of liquidity.

Since changes in liquidity are often associated with market volatility and market-wide perceptions of risk, which vary across time (see Demsetz (1968), Glosten and Milgrom (1985), Hasbrouck (1988), McInish and Wood (1992), Huang and Stoll (1996), Venkataraman (2001), and Xiong, Sullivan, and Wang (2013)), our first objective is to document the level of time variation in the illiquidity premium. Our second objective is to examine how the illiquidity premium differs across varying levels of investor sentiment. Consistent with much of the prior research, we generally find that stocks that are the least liquid outperform stocks that are the most liquid. However, we also show that a significant illiquidity premium only exists in 11 of the 25 years of our sample and that the variation in the liquidity premium is greater than the liquidity premium itself in some specifications. This initial set of results has important implications. First, the success of investment styles that focus on liquidity is not likely to be persistent across time. Second, liquidity-level triggers that might signal when best to trade or rebalance must consider the time-varying nature of prices that are affected by liquidity.

In our second set of tests, we find the illiquidity premium to be highest during periods of low investor sentiment. That is, when investor sentiment is high, investors are less worried about liquidity, which results in a lower illiquidity premium. Conversely, when investor sentiment is low, market participants focus more attention on the liquidity of assets, and the illiquidity premium is higher. We find that the average return premium during low sentiment periods is three times as great as the average return premium during high sentiment periods.

Understanding this type of time variation in the illiquidity premium is important for those investors that tilt their portfolios toward small, less liquid stocks, or try to capture the illiquidity return premium directly. Moreover, our evidence suggests that a simple strategy of conditioning on investor sentiment improves the returns to a portfolio constructed to take advantage of the illiquidity premium by as much as 2.5% per month, relative to the benchmark. Furthermore, our findings highlight the argument of Li and Sullivan (2011) that active management must have the flexibility to capture shifts in risk and return expectations. While static allocations might capture some of the illiquidity return premium, a better understanding of not only the time-varying nature of that premium but also the underlying factors that contribute to that time variation is valuable.

Data Description

The data used for this study is obtained from several sources. From the Center for Research on Security Prices (CRSP), we gather daily data on bid and ask prices, returns, and volume. From CRSP, we also obtain returns, closing prices, and shares outstanding at the monthly level. We gather annual balance sheet data from Compustat to estimate the book-to-market ratios. When constructing our sample, we require book-to-market ratios, which are calculated as the ratio of book equity to market capitalization, to be positive. We obtain investor sentiment, which was used by Baker and Wurgler (2006), directly from Jeffrey Wurgler's website.[1] Sentiment is the principal component of five proxies of investor sentiment, which include the dividend premium, the closed-end fund discount, the number of Initial Public Offerings (IPOs), the underpricing of IPOs, and the equity share of new issues.[2] We note that bid and ask prices are only available starting in 1993, which limits our sample period. After merging the data, we are left with more than 21,400 unique securities and 2.08 million stock-month observations that span the period from January 1st, 1993 to June 30th, 2018.

Table 1 provides some statistics that summarize the data. Throughout the study, we use two measures of illiquidity. *Spread* is the daily bid-ask spread that has been averaged across months for each stock. The variable is calculated as the difference between the CRSP closing ask price and the closing bid price scaled by the spread midpoint. *Amihud* is a measure of liquidity that is presented in Amihud (2002). It is the ratio of the absolute value of the daily stock return to the dollar trading volume (in 100,000s). We note that the *Amihud* measure is calculated using daily returns and daily volume but averaged across each month. The first two rows of Table 1 show that the average stock has a spread of 2.72% and Amihud illiquidity of 0.7329.

Although Amihud's illiquidity measure is one of the most widely used proxies for liquidity in academic research, several recent papers have examined Amihud's illiquidity more closely and compared it with other proxies for liquidity. Lou and Shu (2017) use high-frequency data to confirm that the Amihud (2002) measure does a good job of capturing stock liquidity and price impact, however, they also state that caution should be used when the Amihud measure is employed to examine liquidity premium because it does not appear that Amihud's measure is compensation for price impact. Furthermore, Drienko, Smith, and Von Reibnitz (2019), Harris and Amato (2019), and Amihud (2019) discuss the merits, interpretations, and consistency of the Amihud (2002) measure of illiquidity. Drienko, Smith, and Von Reibnitz (2019) highlight the fact that technological changes have reduced transaction costs and increased liquidity, which have led to a decline in the sensitivity of investors to illiquidity risk. Harris and Amato (2019), similar to Lou and Shu (2017) find that Amihud's measure of illiquidity is driven by its trading component and argue that the ratio of the mean daily absolute return to mean daily trading volume is easier to calculate and provides the same explanatory value.[3] Amihud (2019) defends the illiquidity measure used in Amihud (2002) and shows that a factor created using that measure has a positive and significant risk-adjusted return for more than 60 years. Given the debate over Amihud's (2002) measure of illiquidity, we focus our attention on bid-ask spreads as well as the traditional measure of Amihud's (2002) illiquidity. We also incorporate measures of liquidity risk from Acharya and Pedersen (2005) to account for the commonality in liquidity. The first liquidity risk measure is COV(Sp,MKTSp), the covariance between individual stock liquidity and market liquidity. The second measure used in Acharya and Pedersen (2005) is COV(Ret,MKTSp), which is defined as the covariance between a security's return and market liquidity. The third liquidity risk measure is COV(Sp,MKTRet), or the covariance between a security's liquidity and the market return. These measures help us understand whether our findings relative to our liquidity measures are driven by the commonality in liquidity observed through liquidity risk proxies.

We also include summary statistics for several other variables that are used throughout the analysis. Beta is the CAPM beta that is estimated using daily returns for each stock and the returns for the value-weighted CRSP index for each stock, each month. We note that to obtain accurate estimates for Beta, we use rolling six-month windows in our estimation of the CAPM. Size is the market capitalization on the last day of each month (in $billions). B/M is the book-to-market ratio. Momentum is the cumulative return from month *t*-12 to *t*-2, where month *t* is the current trading month. The average stock has a beta of 0.7793, market capitalization of $2.89 million, a book-to-market ratio of 0.51, and momentum of 13.9%, on average.[4]

Time-Varying Liquidity Premia

Droughts in liquidity often accompany a crisis or periods of high volatility. In fact, the lack of liquidity has been at the root of financial market turmoil and increased volatility in recent years. As market conditions change, liquidity providers demand differing expected returns for providing liquidity. Demsetz (1968) posits that because liquidity providers hold an inventory of potentially volatile securities, they face the risk of the possibility that stocks might decrease in price and therefore widen bid-ask spreads to be compensated for that risk. Empirical evidence seems to confirm this idea (see McInish and Wood (1992), Huang and Stoll (1996), and Venkataraman (2001)). Prior research has already documented that liquidity might vary across time. For instance, Baker and Stein (2004) provide a theoretical argument that liquidity will vary across time. They examine how market liquidity measures vary across time and use dynamic liquidity information to adjust asset allocations. They measure illiquidity following Amihud (2002) and document changes in liquidity from 1980 to 2010. Given the time-varying nature of liquidity, it would seem plausible that the return premium associated with illiquidity might also vary across time. However, the relation between illiquidity and the premium associated with illiquidity may be more subtle. Xiong, Sullivan, and Wang (2013) argue that market makers will require higher expected returns when providing liquidity during periods of market turmoil. In the presence of such turmoil, liquidity providers will likely widen bid-ask spreads. By construction, those who choose to invest during these periods will do so at worse prices than during more normal periods. Therefore, the time variation of the illiquidity premium is not likely to be explained simply by periods of volatility or market turmoil because, holding all else constant, a mere lack of liquidity will result in higher returns for market makers and lower returns for investors. Additionally, Watanabe and Watanabe (2008) find that liquidity risk varies through time and that high liquidity-beta states are characterized by heavy trade, high volume, and wide cross-sectional dispersion in liquidity betas. They attribute this time variation to liquidity risk in which investors face uncertainty related to counterparty preferences.

Table 2 reports the variation of our liquidity measures through time. The average *Spread* ranges from .0043 in 2018 to .0625 in 1993. As previously documented in Roll and Subrahmanyam (2010), spreads have been steadily declining for decades. Column 2 reports the time-series variation for Amihud's (2002) measure of illiquidity. *Amihud* ranges from a low of .1046 in 2018 to a high of 2.4120 in 1993. Although the trend of decreasing illiquidity is also evident using Amihud's measure, we can more clearly see the droughts in liquidity that have occurred during the recent financial crisis. Spikes in illiquidity in both 2001–2002 (Technology Bubble Correction) and 2008–2009 (Financial Crisis) highlight the relation between illiquidity and market turmoil (Xiong, Sullivan, and Wang (2013)). Although examining liquidity directly is informative, it is important to remember the distinction between the illiquidity premium and illiquidity. Thus, the next step in our analysis is to examine the time-varying nature of the relation between returns and illiquidity more directly.

Table 3 details the illiquidity premium over our entire sample. To examine the relation between illiquidity and returns, we estimate the following regression using pooled, stock-month data.

$$R_{i,t+1} = \alpha + \beta_1 Beta_{i,t} + \beta_2 Size_{i,t} + \beta_3 B/M_{i,t} + \beta_4 Momentum_{i,t} + \beta_5 Liquidity_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

The dependent variable in our analysis is the return for stock i in month $t+1$. We estimate the equation using a traditional Fama and MacBeth (1973) approach. Column 1 of Table 3 reports the coefficients from a simple regression of next-month returns on *Spread*. *Spread* is the average daily bid-ask spread for each stock during each month. As expected, we see a large positive coefficient that is both economically and statistically significant. Column 2 of Table 3 includes additional control variables that have been shown to impact next month returns. While the coefficient on *Spread* decreases from 0.1353 to 0.1247, the relation between illiquidity remains substantial and significant. We note that the t-statistics reported in Table 3 (and those that follow) are obtained from standard errors that are corrected using the Newey and West (1987) procedure that accounts for three lags. Columns 3 and 4 report results from similar regressions, but use Amihud's (2002) measure of illiquidity instead of spreads. Although the magnitude of the premium associated with illiquidity is much smaller using Amihud's measure, this is not surprising since it is calculated using the absolute value of the return. With next month's return as our dependent variable, using a measure of illiquidity that is a function of this month's return will also capture some of the known autocorrelation that is present in stock returns. Nevertheless, our findings are robust to several different definitions of illiquidity and we discuss the robustness of our findings in more detail in a subsequent section.

Although the illiquidity premium is quite robust over our entire sample, it is not clear how much the illiquidity premium varies during this period. Table 4 reports the results from Fama-MacBeth (1973) regressions by year. Columns 1 and 2 report coefficients and robust t-statistics when using *Spread* as our proxy for illiquidity. Columns 3 and 4 report coefficients and t-statistics when using *Amihud*. Not only is there substantial variation in the relation between next month's returns and illiquidity, but at times, there is almost a liquidity premium instead of an illiquidity premium. Estimated coefficients on *Spread* range from −0.1891 in 2009 to 0.4307 in 2003. Similarly, coefficients on *Amihud* range from −0.0002 in 2014 to 0.0052 in 2018. This simple analysis highlights the difference between illiquidity and the illiquidity premium. Although liquidity providers will demand a higher expected return for illiquid assets during market turmoil, on average, the return premium associated with illiquidity is, perhaps, by construction, different than the levels of illiquidity during these crisis periods. For example, while 2001 to 2002 and 2008 to 2009 are the most illiquid, they also exhibit the lowest premiums paid for taking on the risk of illiquidity.

Investor Sentiment and Liquidity

Given that we want to invest in illiquid assets when the premium set by the market is the highest, it is important to understand some of the possible contributors to the time variation in the illiquidity premium. Since the anecdotal evidence suggests that the illiquidity premium does not simply vary across the business cycle, we next attempt to identify other explanations for the time variation found in the return premium. In particular, we attempt to determine whether the time-varying illiquidity premium is explained by investor sentiment. The motivation to do so is based on findings in Antoniou, Doukas, and Subrahmanyam (2013) that show that the return premium associated with momentum is driven almost entirely by high investor sentiment states—particularly in up markets. The argument made by Antoniou, Doukas, and Subrahmanyam (2013) is that investor sentiment causes cognitive dissonance, which slows the diffusion of news into stock prices. In the framework of our study, the optimism that stems from periods of high investor sentiment might reduce the ability of investors to accurately price illiquidity. On the contrary, during low sentiment states, investors are more likely to focus on a broader set of risks associated with the investment. Given this simple argument, we expect to find the illiquidity return premium to be highest in low sentiment states and lowest in high sentiment states.

Figure 1: The figure shows investor sentiment and our two liquidity measures—average daily bid-ask spreads and average daily illiquidity—across the sample period.

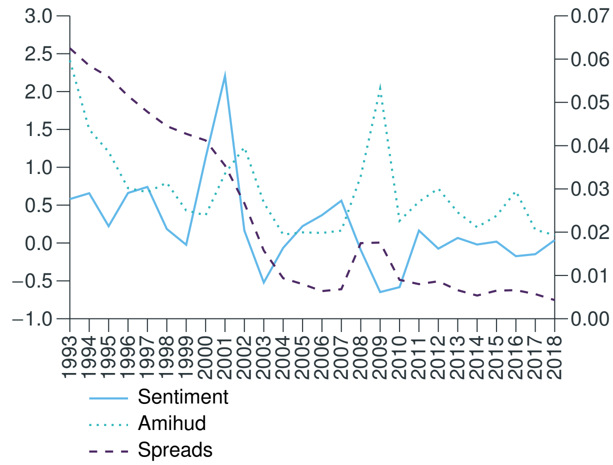

Figure 2: The figure shows investor sentiment, the Fama-MacBeth (1973) coefficient on Spreads, and the Fama-MacBeth (1973) coefficient on *Amihud* across our sample period.

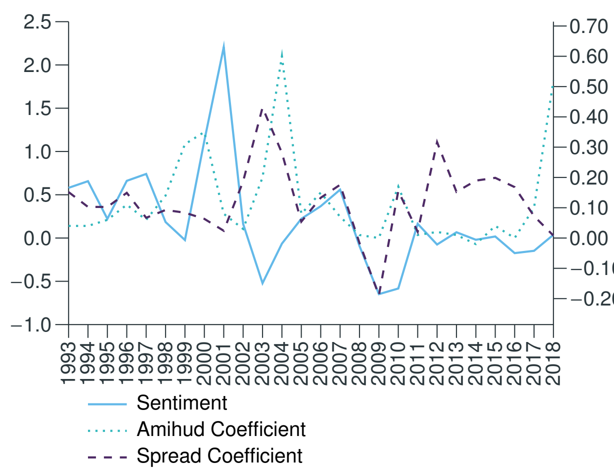

Figure 1 graphically demonstrates the time variation in investor sentiment and measures of illiquidity. Monthly measures of Spread, Amihud's Illiquidity, and Investor Sentiment are plotted from 1993 to 2018. Spikes in both illiquidity and investor sentiment are clear. It also appears that the movements in investor sentiment and illiquidity are not contemporaneously related. Figure 2 is similar to Figure 1 but depicts the time variation in the illiquidity return premium instead of the level of illiquidity (obtained from Table 4). Visually, there appears to be a negative relationship between investor sentiment and the illiquidity return premium. When investor sentiment is low, the liquidity premium is high.

Next, we examine the relation between next-month returns and illiquidity while conditioning on investor sentiment. Table 5 reports results from estimating Equation (1) after sorting months into three sentiment states—similar to Antoniou, Doukas, and Subrahmanyam (2013). Each month is ranked into a tercile based on the level of investor sentiment (following Baker and Stein (2004)) that month and then we estimate Equation (1) using Fama-MacBeth (1973) regressions across each tercile. Results are reported that use both *Spread* and *Amihud* as proxies for illiquidity. Columns 1 and 2 of Table 5 report estimates for the low sentiment state. Columns 3 and 4 report estimates for the medium sentiment state. Finally, Columns 5 and 6 report estimates for the high sentiment state. As before, we also include control variables that capture empirical relations that have been documented concerning the cross-section of expected stock returns. In the low sentiment periods, the coefficient on *Spread* is 0.1622 with a *t*-statistic of 2.77, which corresponds to a statistical significance level less than .01. As sentiment increases, the return premium on illiquidity decreases. Medium investor sentiment periods have a coefficient of 0.1238 (*t*-statistic = 2.93) and high investor sentiment periods have an illiquidity premium of 0.0954 (*t*-statistic = 3.74). This finding is not only statistically significant but also economically meaningful in that the illiquidity return premium is approximately two times greater in low sentiment periods than in high sentiment periods. We also include the measures of liquidity risk from Acharya and Pedersen (2005) to account for the commonality in liquidity. We report coefficients for COV(Sp,MKTSp), the covariance between individual stock liquidity and market liquidity, COV(Ret,MKTSp), the covariance between a security's return and market liquidity, and COV(Sp,MKTRet), the covariance between a security's liquidity and the market return. None of the coefficient estimates on the included covariance measures are significant and they do not diminish the strength of our findings with respect to *Spread* and *Amihud*. This multivariate analysis confirms our suspicions from Figure 2 and highlights the negative relation between investor sentiment and the illiquidity return premium while controlling for a number of related factors.

Similar results can be seen when using Amihud's (2002) illiquidity measure. The estimated coefficient in the low sentiment state is about twice as large as the estimated coefficient in high sentiment periods. Our results are consistent across multiple proxies for illiquidity and support the notion that investor sentiment is inversely related to the return premium associated with illiquid stocks. Furthermore, we can see that the liquidity risk measures from Acharya and Pedersen (2005) that capture the covariance between returns and liquidity are not statistically significant and do not explain the time-varying component of liquidity that is related to investor sentiment.

One of the drawbacks of using the Wurgler measure of investor sentiment is that it is estimated from other market measures that make it less timely to active trading strategies. Another possible measure of investor sentiment is the VIX volatility index, which measures the expected price fluctuations in S&P 500 Index options. Changes in VIX are often associated with changes in risk, fear, or stress in the market. So in addition to using Wurgler's investor sentiment measure, we also examine liquidity premiums relative to changes in VIX. Table 6 is similar to Table 5 but uses terciles based on changes in VIX instead of Wurgler's investor sentiment. A high percent change in VIX would be indicative of *low* investor sentiment and small changes in VIX would indicate calm periods in the market or *high* investor sentiment. Similar to Table 5, we find coefficients on *Spread* and *Amihud* are monotonically decreasing from low sentiment periods to high sentiment periods. Columns 1 and 2 report the results for the tercile of High % change in VIX. Column 1 includes *Spread* as our measure of liquidity with a coefficient of 0.2989 and a *t*-statistic of 5.07. Column 2 reports results where *Amihud* is our proxy for liquidity. The coefficient on *Amihud* is 0.0020 with a *t*-statistic of 2.70. In contrast, the coefficients on *Spread* and *Amihud* in Columns 5 and 6 are much smaller and in the case of *Spread*, insignificantly different from zero. Using VIX as a proxy for investor sentiment demonstrates the robustness of the relation between sentiment and liquidity and is directly observable, which allows it to be implemented in real-time trading strategies.

Portfolio Implications

Our findings that the return premium associated with illiquid stocks is time-varying and highly correlated with investor sentiment has implications for anyone that attempts to benefit from the illiquidity return premium in their portfolio. Although the timing of trades or adjusting the allocation of assets as market liquidity changes can add value, understanding the fact that the premium the market places on illiquid stocks and illiquidity itself are not perfectly correlated can provide additional value. Next, we examine returns in a portfolio setting to better quantify the added value that an investor could receive by conditioning the illiquidity return premium on investor sentiment. We note that when sorting our data into three sentiment states, our portfolio time series are discontinuous.

Table 7 reports the results from several portfolios. In particular, the exhibit provides average monthly returns for equal-weighted and value-weighted portfolios formed (and rebalanced) each month on stocks with the highest (highest quintile) bid-ask spread (Panel A) and stocks with the highest (highest quintile) Amihud (2002) illiquidity (Panel B). As a benchmark, we include the S&P 500 index return. In the final two columns of the exhibit, we report the differences between the equal-weighted and value-weighted portfolios respectively, and the S&P 500 benchmark. The objective here is to determine whether the performance of portfolios sorted on measures of illiquidity—relative to an appropriate benchmark—is driven by periods of low sentiment. Panel A shows that monthly returns to the equal-weighted portfolio beat the S&P 500 generally (row 1). Furthermore, the performance of both the equal-weighted and value-weighted portfolios decreases monotonically across increasing investor sentiment states. Columns 4 and 5 show the excess returns of the various portfolios. Here, we see that the equal-weighted portfolio outperforms the S&P 500 index in low sentiment states by approximately 1.77% per month. The outperformance of the value-weighted portfolio is slightly more than 1% per month in the low sentiment state. On the contrary, results suggest that neither the equal-weighted nor the value-weighted portfolio outperform the benchmark in the high sentiment state. Similar results are found in Panel B when we examine portfolios based on Amihud's (2002) illiquidity instead of bid-ask spreads. These results seem to confirm our findings in Table 5 and indicate that the return premium associated with illiquidity is driven by periods of low investor sentiment.

Robustness

To verify the robustness of our findings, we perform a variety of tests that are not tabulated in the paper. First, we conduct several tests using different model specifications and find that, similar to the results reported in the paper, the illiquidity return premium has an important time-varying component that seems to be well explained by investor sentiment.

Second, as noted above, we begin our sample in 1993 given the data limitations for bid- and ask-prices in CRSP. Using Amihud's (2002) measure of illiquidity, we replicate our analysis beginning in 1980 instead of 1993 and find a significant return premium associated with illiquidity for the entire sample period. Second, we also find that the return premium varies substantially across time. Further, the illiquidity premium is significant during periods of low investor sentiment but not significant during the high sentiment states. We also examine alternative proxies for liquidity including turnover, volume, and mean return divided by mean volume with similar results.

Conclusion

Understanding the time-varying nature of the illiquidity return premium cannot only help one understand the role of liquidity in the marketplace but can also aid in portfolio construction. We document the time variation in the illiquidity return premium and find that it can vary dramatically from year to year. We also find that the illiquidity return premium is related to investor sentiment. When investor sentiment is high, illiquidity premiums are low and when investor sentiment is low, illiquidity premiums are high. This fact, in and of itself, can help exploit the illiquidity return premium because it is not dependent on the estimation of liquidity—by the time you have measured changes in the average market liquidity, it might be too late to take advantage of those changes in a portfolio setting. Furthermore, we find that the added benefit to not only conditioning on illiquidity but also considering investor sentiment is worthwhile. Understanding factors that impact liquidity and the illiquidity return premium are also important because changes in market liquidity are related to the business cycle and stock market liquidity is a good leading indicator of the real economy (see Næs, Skjeltorp, and Ødegaard (2011)).

Table 1: Summary Statistics. The exhibit reports statistics that describe our sample. Spread is the average daily bid-ask spread for each stock during each month. Similarly, Amihud is the Amihud (2002) measure of daily illiquidity or the ratio of the absolute value of the daily return scaled by trading volume (in 100,000s). We, again, average daily Amihud for each stock during each month of our sample period. Beta is the CAPM beta that is estimated using daily returns for each stock and the returns for the value-weighted CRSP index for each stock, each month. We note that to obtain accurate estimates for Beta, we use rolling six-month windows in our estimation of the CAPM. Size is the market capitalization on the last day of each month (in $billions). B/M is the book-to-market ratio. Momentum is the cumulative return from month *t*-12 to *t*-2, where month *t* is the current trading month.

	Mean	Std. Deviation	25th Percentile	Median	75th Percentile
	1	2	3	4	5
Spread	0.0272	0.0511	0.0020	0.0111	0.0321
Amihud	0.7329	16.4039	0.0003	0.0034	0.0596
Beta	0.7793	2.4827	0.1400	0.7430	1.3901
Size	2.8856	14.9961	0.0501	0.2232	1.0874
B/M	0.5048	43.0776	0.0323	0.0596	0.1001
Momentum	0.1386	0.5697	–0.1267	0.1187	0.3610

Table 2: Summary Statistics. The exhibit reports statistics about our measures of liquidity in each year across the sample period. Spread is the average daily bid-ask spread for each stock during each month. Similarly, Amihud is the Amihud (2002) measure of daily illiquidity or the ratio of the absolute value of the daily return scaled by trading volume (in 100,000s). We, again, average daily Amihud for each stock during each month of our sample period.

	Spreads	Amihud
	1	2
1993	0.0625	2.4120
1994	0.0585	1.4989
1995	0.0559	1.2041
1996	0.0515	0.7247
1997	0.0478	0.6720
1998	0.0445	0.7961
1999	0.0427	0.4295
2000	0.0412	0.3662
2001	0.0354	0.9153
2002	0.0267	1.2656
2003	0.0158	0.5337
2004	0.0093	0.1115
2005	0.0080	0.1403
2006	0.0064	0.1331
2007	0.0068	0.1629
2008	0.0175	0.8825
2009	0.0176	2.0373
2010	0.0090	0.2932
2011	0.0080	0.5446
2012	0.0087	0.7191
2013	0.0066	0.4053
2014	0.0054	0.2088
2015	0.0065	0.3592
2016	0.0066	0.6865
2017	0.0057	0.1743
2018	0.0043	0.1046
Average	0.0234	0.6839
Std. Dev.	0.0201	0.5920

Table 3: Fama-MacBeth Regressions. The exhibit reports the results from estimating the following equation using pooled stock-month data.

$$R_{i,t+1} = \alpha + \beta_1 Beta_{i,t} + \beta_2 Size_{i,t} + \beta_3 B/M_{i,t} + \beta_4 Momentum_{i,t} + \beta_5 Liquidity_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the return for stock i in month $t+1$. The independent variables include the following. Beta is the CAPM beta that is estimated using daily returns for each stock and the returns for the value-weighted CRSP index for each stock, each month. We note that to obtain accurate estimates for Beta, we use rolling six-month windows in our estimation of the CAPM. Size is the market capitalization on the last day of each month (in $billions). B/M is the book-to-market ratio. Momentum is the cumulative return from month t-12 to t-2, where month t is the current trading month. The independent variable of interest is one of our two measures of liquidity. Spread is the average daily bid-ask spread for each stock during each month. Similarly, Amihud is the Amihud (2002) measure of daily illiquidity or the ratio of the absolute value of the daily return scaled by trading volume (in 100,000s). We estimate the equation using a traditional Fama and MacBeth (1973) approach. We note that t-statistics from robust Newey and West (1987) standard errors that account for three lags are reported in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 levels, respectively.

	1	2	3	4
Intercept	0.0085** (2.53)	0.0265** (2.29)	0.0110*** (3.16)	0.0413*** (3.51)
Beta		0.0000 (0.01)		0.0000 (−0.05)
Size		0.0050*** (6.78)		0.0049*** (6.72)
B/M		−0.0002 (−0.45)		−0.0009* (−1.66)
Momentum		0.0022 (1.19)		0.0018 (0.99)
Spread	0.1353*** (4.11)	0.1247*** (4.90)		
Amihud			0.0013*** (3.43)	0.0011*** (3.68)

Table 4: Fama and MacBeth (1973) Regressions by Year. The exhibit reports the results from estimating the following equation using pooled stock-month data for each year in our sample period.

$$R_{i,t+1} = \alpha + \beta_1 Beta_{i,t} + \beta_2 Size_{i,t} + \beta_3 B/M_{i,t} + \beta_4 Momentum_{i,t} + \beta_5 Liquidity_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the return for stock i in month $t+1$. The independent variables include the following. Beta is the CAPM beta that is estimated using daily returns for each stock and the returns for the value-weighted CRSP index for each stock, each month. We note that to obtain accurate estimates for Beta, we use rolling six-month windows in our estimation of the CAPM. Size is the market capitalization on the last day of each month (in $billions). B/M is the book-to-market ratio. Momentum is the cumulative return from month t-12 to t-2, where month t is the current trading month. The independent variable of interest is one of our two measures of liquidity. Spread is the average daily bid-ask spread for each stock during each month. Similarly, Amihud is the Amihud (2002) measure of daily illiquidity or the ratio of the absolute value of the daily return scaled by trading volume (in 100,000s). We estimate the equation using a traditional Fama and MacBeth (1973) approach for each year. Column 1 reports the coefficients on Spreads while Column 3 shows the coefficients on Illiquidity. We note that t-statistics from robust Newey and West (1987) standard errors that account for three lags are reported in Columns 2 and 4. *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 levels, respectively.

	Spread Coefficient	*t*-statistic	Amihud Coefficient	*t*-statistic
	1	2	3	4
1993	0.1517***	2.82	0.0004***	3.05
1994	0.1027	1.58	0.0004*	1.71
1995	0.1026**	2.16	0.0006	1.55
1996	0.1492**	2.00	0.0011***	2.66
1997	0.0668	1.55	0.0006*	1.88
1998	0.0926*	1.80	0.0014***	2.58
1999	0.0837*	1.72	0.0031***	3.13
2000	0.0632	0.92	0.0035*	1.84
2001	0.0240	0.32	0.0008	1.59
2002	0.1871**	2.18	0.0003**	2.08
2003	0.4307***	4.68	0.0020***	3.70
2004	0.2811*	1.74	0.0060	1.13
2005	0.0541	0.30	0.0008	0.64
2006	0.1329	1.01	0.0015	1.53
2007	0.1758	1.36	0.0007	0.65
2008	–0.0167	–0.16	0.0001	0.48
2009	–0.1891	–1.18	0.0000	0.12
2010	0.1553	0.63	0.0017*	1.65
2011	0.0208	0.22	0.0001	0.76
2012	0.3165	1.59	0.0002	0.98
2013	0.1525	0.83	0.0001	0.29
2014	0.1896	0.71	–0.0002	–0.30
2015	0.1987	1.00	0.0004	1.52
2016	0.1681	0.89	0.0000	–0.11
2017	0.0724	0.44	0.0010	0.64
2018	0.0079	0.02	0.0052**	2.16
Average	0.1221		0.0012	
Std. Dev.	0.1178		0.0016	

Table 5: Fama and MacBeth (1973) Regressions by Investor Sentiment. The exhibit reports the results from estimating the following equation using pooled stock-month data for three investor sentiment states.

$$R_{i,t+1} = \alpha + \beta_1 Beta_{i,t} + \beta_2 Size_{i,t} + \beta_3 B/M_{i,t} + \beta_4 Momentum_{i,t} + \beta_5 Liquidity_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the return for stock i in month $t+1$. The independent variables include the following. Beta is the CAPM beta that is estimated using daily returns for each stock and the returns for the value-weighted CRSP index for each stock, each month. We note that to obtain accurate estimates for Beta, we use rolling six-month windows in our estimation of the CAPM. Size is the market capitalization on the last day of each month (in $billions). B/M is the book-to-market ratio. Momentum is the cumulative return from month t-12 to t-2, where month t is the current trading month. The independent variable of interest is one of our two measures of liquidity. Spread is the average daily bid-ask spread for each stock during each month. Similarly, Amihud is the Amihud (2002) measure of daily illiquidity or the ratio of the absolute value of the daily return scaled by trading volume (in 100,000s). We incorporate liquidity risk measures from Acharya and Pedersen (2005), which include COV(Sp,MKTSp), the covariance between individual stock liquidity and market liquidity. COV(Ret,MKTSp) is the covariance between a security's return and market liquidity. The third liquidity risk measure is COV(Sp,MKTRet), or the covariance between a security's liquidity and the market return. We estimate the equation using a traditional Fama and MacBeth (1973) approach for three sentiment states. Low Sentiment is the state in which investor sentiment is in the lowest tercile while Medium (High) Sentiment is the state in which investor sentiment is in the medium (highest) tercile. We note that t-statistics from robust Newey and West (1987) standard errors that account for three lags are reported in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 levels, respectively.

	Low Sentiment		Medium Sentiment		High Sentiment	
	1	2	3	4	5	6
Intercept	0.0556 (2.89)	0.0655 (3.44)	0.0102 (0.63)	0.0267 (1.59)	0.0093 (0.52)	0.0292 (1.50)
Beta	−0.0001 (−0.02)	−0.0001 (−0.03)	0.0002 (0.19)	0.0002 (0.12)	−0.0009 (−0.58)	−0.0010 (−0.63)
Size	−0.0018 (−2.13)	−0.0022 (−2.62)	0.0001 (0.18)	−0.0006 (−0.84)	0.0012 (1.35)	0.0003 (0.31)
B/M	0.0030 (3.46)	0.0030 (3.41)	0.0032 (4.17)	0.0032 (4.11)	0.0092 (7.94)	0.0091 (7.93)
Momentum	−0.0027 (−0.68)	−0.0029 (−0.73)	0.0063 (3.76)	0.0058 (3.52)	0.0035 (1.38)	0.0029 (1.17)
COV(Sp,MKTSp)	−1.5409 (−0.38)	5.2939 (0.81)	−1.9625 (−0.41)	1.6203 (0.38)	0.2339 (0.56)	0.2537 (0.62)
COV(Ret,MKTSp)	0.3143 (0.15)	0.1620 (0.08)	0.8696 (0.35)	0.9649 (0.40)	−0.5754 (−1.23)	−0.5233 (−1.12)
COV(Sp,MKTRet)	0.0193 (0.62)	0.0376 (0.99)	0.0199 (0.93)	0.0233 (1.07)	0.0443 (1.73)	0.0419 (1.71)
Spread	0.1622 (2.77)		0.1238 (2.93)		0.0954 (3.74)	
Amihud		0.0017 (2.37)		0.0008 (2.63)		0.0009 (2.38)

Table 6: Fama and MacBeth (1973) Regressions by Investor Sentiment (VIX). The exhibit reports the results from estimating the following equation using pooled stock-month data for three investor sentiment states.

$$R_{i,t+1} = \alpha + \beta_1 Beta_{i,t} + \beta_2 Size_{i,t} + \beta_3 B/M_{i,t} + \beta_4 Momentum_{i,t} + \beta_5 Liquidity_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the return for stock i in month $t+1$. The independent variables include the following. Beta is the CAPM beta that is estimated using daily returns for each stock and the returns for the value-weighted CRSP index for each stock, each month. We note that to obtain accurate estimates for Beta, we use rolling six- month windows in our estimation of the CAPM. Size is the market capitalization on the last day of each month (in $billions). B/M is the book-to-market ratio. Momentum is the cumulative return from month t-12 to t-2, where month t is the current trading month. The independent variable of interest is one of our two measures of liquidity. Spread is the average daily bid-ask spread for each stock during each month. Similarly, Amihud is the Amihud (2002) measure of daily illiquidity or the ratio of the absolute value of the daily return scaled by trading volume (in 100,000s). We estimate the equation using a traditional Fama and MacBeth (1973) approach for three sentiment states. Low Sentiment is the state in which the % change in VIX is in the lowest tercile while Medium (High) Sentiment is the state in which the % change in VIX is in the medium (highest) tercile. We note that t-statistics from robust Newey and West (1987) standard errors that account for three lags are reported in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 levels, respectively.

	Low Sentiment High %ΔVIX		Medium Sentiment Medium %ΔVIX		High Sentiment Low %ΔVIX	
	1	2	3	4	5	6
Intercept	−0.0135 (−0.82)	0.0170 (0.95)	0.0516 (2.43)	0.0555 (2.54)	0.0516 (2.43)	0.0555 (2.54)
Beta	−0.0074 (−3.66)	−0.0079 (−3.88)	0.0066 (3.22)	0.0069 (3.32)	0.0066 (3.22)	0.0069 (3.32)
Size	0.0006 (0.75)	−0.0008 (−0.88)	−0.0004 (−0.39)	−0.0006 (−0.56)	−0.0004 (−0.39)	−0.0006 (−0.56)
B/M	0.0056 (4.85)	0.0055 (4.80)	0.0057 (6.08)	0.0056 (5.99)	0.0057 (6.08)	0.0056 (5.99)
Momentum	0.0012 (0.48)	0.0006 (0.24)	0.0007 (0.20)	0.0005 (0.14)	0.0007 (0.20)	0.0005 (0.14)
Spread	0.2989 (5.07)		0.0182 (0.37)		0.0182 (0.37)	
Amihud		0.0020 (2.70)		0.0005 (2.24)		0.0005 (2.24)

Table 7: The exhibit reports equal-weighted and value-weighted portfolios formed (and rebalanced) each month on stocks with the highest (highest quintile) bid-ask spread (Panel A) and stocks with the highest (highest quintile) Amihud (2002) illiquidity (Panel B). As a benchmark, the exhibit provides the S&P 500 index return. In the final two columns of the exhibit, we report the differences between the equal-weighted and value-weighted portfolios and the benchmark. *T*-statistics are provided in parentheses, which test whether the differences are significantly different from zero. *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 levels, respectively.

Panel A. Equal-Weighted and Value-Weighted Spread Portfolio Performance

	EW Portfolio Returns	VW Portfolio Returns	S&P 500 Returns	1–3	2–3
	1	2	3	4	5
All Observations	0.0145	0.0078	0.0068	0.0077** (2.00)	0.0010 (0.28)
Low Sentiment	0.0260	0.0186	0.0082	0.0177*** (2.89)	0.0104* (1.69)
Med. Sentiment	0.0072	0.0009	0.0092	–0.0020 (–0.36)	–0.0083 (–1.49)
High Sentiment	0.0098	0.0035	0.0028	0.0070 (0.88)	0.0008 (0.13)

Panel B. Equal-Weighted and Value-Weighted Amihud Portfolio Performance

	EW Portfolio Returns	VW Portfolio Returns	S&P 500 Returns	1–3	2–3
	1	2	3	4	5
All Observations	0.0143	0.0062	0.0068	0.0075** (2.22)	–0.0006 (–0.22)
Low Sentiment	0.0241	0.0165	0.0082	0.0159*** (2.83)	0.0082 (1.58)
Med. Sentiment	0.0072	–0.0012	0.0092	–0.0020 (–0.39)	–0.0104* (–1.94)
High Sentiment	0.0114	0.0030	0.0028	0.0086 (1.29)	0.0002 (0.04)

Notes

1. http://people.stern.nyu.edu/jwurgler/

2. It is worth noting that the original measure from Baker and Wurgler (2006) included NYSE turnover as one of the variables used to estimate a principal component for sentiment, however, their updated measure does not include turnover because of the increased trading related to high-frequency traders. This is actually quite helpful in our analysis because some liquidity proxies are constructed using trading volume, which could result in a mechanical relationship between the two.

3. We find almost identical results to those reported in unreported robustness tests that use the ratio of the mean daily absolute return to the mean daily trading volume instead of Amihud's (2002) measure.

4. The average Beta differs from 1 because we calculate arithmetic averages instead of value-weighted averages for our summary statistics.

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