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The maximum bid-ask spread

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ABSTRACT

We examine the return premium associated with a new measure of illiquidity that focuses on extreme points in the distribution of bid-ask spreads. Results show that stocks with larger maximum bid-ask spreads and price impacts command a return premium that is both statistically and economically significant. These results are robust to a series of multifactor portfolio tests and cross-sectional regressions controlling for mean spreads and other observable liquidity metrics. These findings suggest that the distribution of spreads matters when identifying illiquidity return premia due to the multi-faceted nature of liquidity.

1. Introduction

Although innovations have dramatically improved the quality of financial markets over the past few decades, the recent financial crisis was a stark reminder of the importance of liquidity to a well-functioning market. Historically, the spread between the bid and ask prices has been one of the most common proxies of liquidity. Amihud and Mendelson (1986) show both theoretically and empirically that expected returns are a positive, concave function of bid-ask spreads. The idea of a return premium associated with the lack of liquidity is intuitive. Investors are likely to demand higher returns as compensation for the risk of not being able to liquidate their position in a timely and cost-efficient manner. Empirically, this illiquidity premium has been documented in a variety of settings (e.g., Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Datar et al., 1998; Liu, 2006; Han and Lesmond, 2011).

While liquidity is generally defined as the ability to trade in a reasonable amount of time and at a low cost (Pástor and Stambaugh, 2003), there are multiple dimensions that determine the liquidity of a security. The depth of the limit order book, the speed at which one can trade, and the time-varying nature of liquidity are dimensions not necessarily captured in the bid-ask spread. Given its importance, a variety of measures have been developed to try and better capture the liquidity of stocks. Amihud (2002) measures illiquidity in a way that accounts for the price impact of trades and, empirically, leads to higher expected returns. Pástor and Stambaugh (2003) form a market-wide liquidity factor that buys illiquid stocks and sells

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liquid stocks. Lower liquidity corresponds to stronger volume-related return reversals. Their findings also support the idea of an illiquidity premium.

Perhaps the need for additional measures of liquidity is due to the fact that bid-ask spreads have been steadily decreasing over the past two decades, primarily due to the decimalization of security prices (Bessembinder, 1999, 2003; Goldstein and Kavajecz, 2000). Roll and Subrahmanyam (2010) also show that while average spreads have decreased across time, the skewness of spreads has been increasing. They argue that the increase in spread skewness is a result of increased competition between market makers, which may reduce the ability of market makers to cross-subsidize periods of higher levels of asymmetric information. Given the fundamental changes to the distribution of spreads (lower mean spreads and higher spread skewness), using mean bid-ask spreads alone to measure liquidity might be misguided.

In this paper, we propose an alternative measure of liquidity: the maximum percentage effective spread during a particular month. This measure appears to better capture the aspects of liquidity for which the market requires compensation.[1] We contend that maximum spreads (max spreads, hereafter) might better explain the return premium associated with illiquidity than mean spreads. The motivation behind this measure is that investors are concerned with sharp spikes in bid-ask spreads even if they are short-lived and temporary. To the extent that this is true, investors will only be willing to buy stocks with higher max spreads at a significant discount. This idea of max spreads to signal the distribution of liquidity is similar to the intuition in Bali et al. (2011), who suggest that the maximum daily returns signal to investors the expected distribution of returns.[2] Persaud (2003) states that there is broad belief among practitioners and regulators that the principal concern about liquidity in financial markets is not the average liquidity level, which has improved over time, but the uncertainty of liquidity.[3] We argue that max spreads, which should account for the temporary spikes (however short-lived) in illiquidity, will capture important characteristics of liquidity uncertainty.

To explore the possible role of max spreads in measuring liquidity, we test whether or not a return premium exists for our new measure of illiquidity. The underlying objective of our study, however, is not to test for an illiquidity premium, per se. Instead, our objective is to determine whether risk-averse investors are concerned about the right tail of the distribution of bid-ask spreads. We use NYSE Monthly Trade and Quote (MTAQ) data to compute the percentage of effective spreads and, for robustness, the percentage of the 5-min price impacts for a broad cross-section of securities during the 2004–2013 period. We find that the average stock in the sample has a mean spread of 0.70% and a max spread of 10.47%, indicating a large degree of variation. Similarly, the average stock has a mean price impact of 0.22% and a max price impact of 11.62%. We also show that the pooled (cross-sectional) correlation coefficient between max spread and mean spread is only 0.3650 (0.6594). Similarly, the pooled and cross-sectional correlations between the max price impact and the mean price impact are 33.11% and 60.44%, respectively. These results suggest that max spreads capture something different than mean spreads.

We begin by examining whether there is a return premium associated with max spreads in a portfolio framework. We find that current-month returns increase monotonically across portfolios sorted into quintiles by the previous month's max spread. In fact, the difference in returns between the extreme max spread portfolios is 110 bps per month, which is both statistically significant and economically meaningful. These results are robust to various measures of returns, such as returns in excess of the risk-free rate and returns adjusted for the value-weighted market return. We also estimate three-factor, four-factor, and five-factor models, where the fifth factor includes different variants of the Pástor and Stambaugh (2003) liquidity risk factors. We find that the differences in alphas between extreme portfolios range from 94 to 106 bps per month, depending on the risk factors included in the model. Our initial findings suggest a significant return premium is associated with max spreads.

For robustness, we analyze the max price impact in an analogous portfolio setting. Again, we find a monotonic increase in current-month raw, excess, and adjusted returns across max price impact portfolios sorted in the prior month. The difference in returns between the extreme max price impact portfolios is 105 bps a month. In a five-factor model, the difference in alphas between the extreme portfolios is at least 91 bps per month. We interpret these findings as evidence of a return premium associated with max price impacts.

We recognize the possibility that the return predictability of max spreads and max price impacts is being driven by other security characteristics, such as market capitalization, volatility, and, perhaps most importantly, other measures of liquidity (e.g., Amihud's (2002) illiquidity). To address this potential concern, we estimate Fama and Macbeth (1973) regressions, where the dependent variable is the raw return and the independent variables are lagged one month. We find a strong, positive relation between lagged max spreads and returns. For instance, after controlling for a number of stock characteristics that might directly affect returns and liquidity, we find that a one standard deviation increase in max spreads is associated with a 17 to 21 bps increase in next-month returns. Similarly, we find that a one standard deviation increase in max price

[1] In a risk-return framework, if we believe that less liquidity creates additional risk to investors, then better measures of liquidity will be more strongly correlated to future returns. In the extreme, one could argue that a measure of illiquidity that is not associated with a return premium is not capturing the risk dimension of liquidity that is important to investors.

[2] While empirical research has shown that the skewness of returns predicts negative returns at the monthly level (Kumar, 2009; Boyer et al., 2009), Bali et al. (2011) argue that skewness is not persistent and therefore, observing positive skewness in the distribution of returns during the current month might not indicate that returns in the upcoming month will be positively skewed. Therefore, the authors use max returns instead of skewness to identify a return skewness premium.

[3] This notion of liquidity uncertainty is also highlighted in Acharya and Pedersen (2005). However, they do not include liquidity uncertainty in their liquidity-adjusted CAPM. They state that “uncertainty about the illiquidity cost is what generates the liquidity risk in this model (p. 379).”

impact is associated with an 11 bps increase in next-month returns, other factors held constant. Thus, our results provide strong evidence that max spreads, both the effective spread and the price impact component of the spread, might be better estimates of the distribution of expected liquidity than mean spreads.

Due to data constraints, our MTAQ sample is limited to a 10-year period. Therefore, we present results using Center for Research on Security Prices (CRSP) closing spreads for the January 1993 to December 2017 period. This extension increases our monthly observation count in our portfolio tests from 119 to 299. Here we estimate CRSP spreads using closing bid and ask prices as in Roll and Subrahmanyam (2010) and Chung and Zhang (2014) and, similar to before, we identify the maximum spread for a particular stock during a given month. We then run portfolio tests where we sort securities into quintiles by max CRSP spreads. Our results show that the difference in returns between extreme max CRSP spread portfolios formed in the previous month is 0.67%. The difference in five-factor alphas between extreme portfolios is at least 1.09%. In addition, we estimate Fama and Macbeth (1973) regressions and find a significant positive relation between lagged max CRSP spreads and returns. Specifically, a one standard deviation increase in max CRSP spreads is associated with a 28 to 46 bps increase in next-month returns.

In our final set of tests, we attempt to disentangle the potential for collinearity issues between max spreads and mean spreads. However, we note that a simple regression of returns on max spreads and mean spreads produces variance inflation factors less than two. Nevertheless, instead of including max spreads as our variable of interest, we include the skewness of bid-ask spreads (Roll and Subrahmanyam, 2010). We find that spread skewness produces positive estimates that are reliably different from zero, suggesting that the non-normality of the distribution of spreads contains predictability in monthly stock returns. These results hold whether we examine the skewness of MTAQ effective spreads or the skewness of CRSP closing spreads. The findings provide further support for the notion that, in the context of the empirical asset pricing literature, max spreads are capturing something quite different than mean spreads (Amihud and Mendelson, 1986).

We contribute to the literature by comparing max spreads to other proxies of illiquidity. If illiquidity is inherently risky, and investors require additional compensation for holding less liquid securities, then better measures of expected liquidity should more accurately capture this relation. To the extent that larger max spreads are associated with greater liquidity uncertainty, and liquidity uncertainty has become a more important dimension of overall liquidity (Persaud, 2003), then our findings suggest that max spreads might be a more robust proxy for liquidity than measures such as mean bid-ask spread.

The remainder of the article is organized as follows. Section 2 describes the data used in the analysis. Section 3 presents the results from our empirical tests. Section 4 provides some concluding remarks.

2. Data description

The data we use are from several sources. From the NYSE MTAQ files, we obtain intraday prices and volume from trades and quotes time-stamped to the nearest second. From CRSP, we obtain daily prices, returns, volume, and market capitalization. From Compustat, we gather balance sheet information in order to calculate the book-to-market ratios.

We apply the following screens to the MTAQ data. Only trades and quotes during normal market hours (quotes between 9:00 a.m. and 4:00 p.m. and trades between 9:30 a.m. and 4:00 p.m.) are considered. Quotes with non-normal conditions are removed (i.e., bid/ask price or bid/ask size is equal to zero or missing). We closely follow Holden and Jacobsen (2014) and calculate the National Best Bid and Offer (NBBO) across all exchanges and across all market makers for any given second, adjusting for withdrawn quotes. We exclude crossed and locked quotes and use interpolated time to match trades with quotes.

From MTAQ, we obtain data for all securities from 2004 to 2013 and merge these data with CRSP and Compustat data.[4] We restrict our sample to securities that have a closing price greater than \$1.[5] Our sample includes 6422 unique securities. The variables of interest throughout the analysis are the maximum percentage effective spread and the maximum percentage price impact for a given stock in a particular month.[6] For a given security, the percent effective spread on the *kth* trade is defined as:

$$Percent\ Effective\ Spread_k = \frac{2D_k(P_k - M_k)}{M_k}, \tag{1}$$

where D_k is an indicator variable that equals $+1$ if the *kth* trade is a buy and -1 if the *kth* trade is a sell, P_k is the price of the *kth* trade, and M_k is the midpoint of the NBBO quotes assigned to the *kth* trade. We use the Lee and Ready (1991) algorithm to determine whether a given trade is a buy or sell. Under this convention, a trade is a buy when $P_k > M_k$, a sell when $P_k < M_k$, and

[4] While we would like to expand our MTAQ sample, we do not have access to daily TAQ files, which begin in 2014.

[5] We conduct additional tests of the return premium associated with max spreads while restricting our sample to stocks with prices less than \$5. Although the results are unreported, we still find that they are consistent with our findings below.

[6] In a somewhat related study, Bali et al. (2011) examine investor preferences for lottery-like returns. To do so, they examine the maximum daily return during a particular period for each stock and show that stocks with the largest max return underperform the stocks with the lowest maximum daily return. These results are consistent with the idea that investors' preferences for lottery-like stocks leads to price premiums and subsequent underperformance. In a similar manner, we test whether investors perceive that the stocks with the largest maximum daily spread have greater liquidity risk given the possibility of future liquidity droughts. Our objective is to determine whether there is a return premium associated with max spreads.

the tick test is used when $P_k = M_k$. The tick test determines a trade is a buy (sell) if the most recent prior trade at a different price was at a lower (higher) price. For a given security, the percentage price impact on the *kth* trade is defined as:

$$Percent\ Price\ Impact_k = \frac{2D_k(M_{k+5} - M_k)}{M_k}, \tag{2}$$

where M_{k+5} is the prevailing midpoint 5-min after the midpoint M_k posts.

Table 1 reports our sample statistics. *MaxESpread* is the maximum percent effective spread during a particular month. The average stock has a max spread of 10.47%, with a standard deviation of 25.47%. *ESpread* is the percent effective spread averaged across each month. The mean spread is 0.70%, while the median is 0.18%. These statistics highlight the large variation in bid-ask spreads as max spreads are nearly 15 times that of mean spreads for the average stock. *MaxPrcImpact* is the maximum percentage price impact during a particular month and *PrcImpact* is the percentage price impact averaged across each month. Similar to the variation in effective spreads, we find that the max price impact is 11.62% and the mean price impact is 0.22% for the average stock.

Amihud is a low-frequency illiquidity measure (scaled by 10^6) defined as the ratio of the absolute value of daily returns scaled by daily dollar trading volume (Amihud, 2002). The average stock has an Amihud illiquidity of 2.4354, with a standard deviation of 38.5964. *Turn* is the share turnover of the average daily volume scaled by shares outstanding. The average daily share turnover in the sample is 0.88%. *Size* is the market capitalization on the last day of each month. The average (median) security in the sample has a market capitalization of $3.8 billion ($473 million). *B/M* is the book-to-market ratio, which has a mean of 0.291 in our sample. *IdioVolt* is the idiosyncratic volatility of the standard deviation of daily residual returns, where residual returns are obtained from estimating a daily Fama and French (1996) and Carhart (1997) four-factor model. *Beta* is the beta estimate obtained from the daily CAPM. The average security has an idiosyncratic volatility of 2.14% and a beta of 1.01.

3. Empirical results

In this section, we present the results from our empirical analysis. We begin by examining whether or not there is a return premium associated with max spreads and max price impacts using a traditional portfolio approach. Specifically, we explore returns in a multifactor framework and compare returns, as well as three-, four-, and five-factor alphas based on portfolios sorted by either max spreads or max price impacts. In a number of these tests, we specifically control for the Pástor and Stambaugh (2003) liquidity risk factors. To more directly control for heterogeneity in firm characteristics, we estimate a series of Fama-MacBeth cross-sectional regressions. Finally, we perform a variety of robustness tests.

3.1. Portfolio analysis: max spread return premium

In this subsection, we examine whether there is a return premium associated with max spreads. We assume that the illiquidity of a stock represents risk that should require compensation and that, given the changing nature of markets in recent years and the various dimensions of liquidity, examining which liquidity proxy best explains whether expected returns

Table 1
Summary statistics for MTAQ sample (2004–2013).
The table describes the security characteristics in the MTAQ sample for the January 2004 to December 2013 sample period. *MaxESpread* is the maximum intraday percentage effective spread during a particular month and is measured as $\boldsymbol{2D_k(price_k - midpoint_k/midpoint_k)}$, where $\boldsymbol{D_k}$ is an indicator variable that equals $+1$ if the kth trade is a buy and -1 if the kth trade is a sell (trade direction is defined as in Lee and Ready (1991)). *ESpread* is the percentage effective spread. *MaxPrcImpact* is the maximum intraday 5-min price impact during a particular calendar month and is defined as $\boldsymbol{2D_k(midpoint_{k+5} - midpoint_k)/midpoint_k}$, where $\boldsymbol{midpoint_{k+5}}$ is the midpoint in force 5 min after the kth trade. *PrcImpact* is the average 5-min price impact. *Amihud* is the measure of price impact from Amihud (2002), which is the scaled ratio of the absolute value of daily returns to daily dollar volume scaled by 10^6. *Turn* is the share turnover of the average daily volume scaled by shares outstanding (in percent). *Size* is the market capitalization on the last day of each month. *B/M* is the book-to-market ratio. *IdioVolt* is the standard deviation of daily residual returns over a rolling six-month period, where residual returns are obtained from estimating a daily Fama and French (1996) and Carhart (1997) four-factor model. *Beta* is the beta estimate obtained from the daily CAPM over a six-month rolling period.

	Mean	Std. Dev.	Median	25th Percentile	75th Percentile
	(1)	(2)	(3)	(4)	(5)
MaxESpread	0.1047	0.2547	0.0628	0.0363	0.1118
ESpread	0.0070	0.0149	0.0018	0.0007	0.0064
MaxPrcImpact	0.1162	0.2828	0.0667	0.0396	0.1172
PrcImpact	0.0022	0.0112	0.0009	0.0004	0.0022
Amihud	2.4354	38.5964	0.0069	0.0009	0.0833
Turn	0.0088	0.0399	0.0054	0.0023	0.0105
Size ($ billions)	3.8433	16.2332	0.4734	0.1243	1.8887
B/M	0.2908	7.4247	0.0586	0.0333	0.0977
IdioVolt	0.0214	0.0189	0.0166	0.0109	0.0261
Beta	1.0084	1.0278	0.9826	0.4615	1.5266

are informative. We examine various measures of current-month returns (and alphas) across portfolios sorted into quintiles by maximum effective spreads in month t-1.

Panel A of Table 2 reports the mean returns, mean excess returns, and mean-adjusted returns in month t. Excess returns are returns in excess of the risk-free rate, which is approximated with one-month U.S. Government T-bill yields. Adjusted returns are the returns for each stock in excess of the CRSP value-weighted market index. We report mean returns across each portfolio. The last column presents the difference in returns between extreme portfolios, along with a corresponding t-statistic in parentheses. We find that all three measures of returns increase monotonically across max spread portfolios. The difference between extreme portfolios is 110 bps a month, which is both statistically significant at the 0.01 level and economically meaningful. However, we recognize the need to control for other risk factors in a multivariate setting.

Panels B and C of Table 2 report the estimated intercept (alpha) from different variants of the following equation:

$$Excess\ Return_{i,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t^j + \varepsilon_{i,t}\,. \tag{3}$$

The dependent variable is the excess return for stock i in month t. The independent variables include the market risk premium (*MRP*), the small-minus-big risk factor (*SMB*), the high-minus-low risk factor (*HML*), the Carhart (1997) up-minus-down risk factor (*UMD*), and one of three Pástor and Stambaugh (2003) liquidity risk factors (*LIQ*). The different liquidity risk factors, *LEVEL*, *INNOV*, and *VWF*, are described in Pástor and Stambaugh (2003). *CAPM Alpha* is the intercept from estimating a CAPM. *FF3F Alpha* is the intercept from estimating the above equation including *MRP*, *SMB*, and *HML* risk factors. *FF4F Alpha* is the estimated intercept from the above equation excluding *LIQ*. 5F *Alpha* is the intercept from estimating the full version of equation (3). We report these alphas across portfolios sorted by max spreads formed in month t-1, along with differences between extreme portfolios with corresponding t-statistics [from White (1980) robust standard errors] in parentheses.

In Panel B of Table 2, we find that the difference in CAPM alphas between extreme portfolios is 96 bps, which is significant at the 0.01 level. Similar differences are shown between extreme portfolios for FF3F alphas and FF4F alphas, 94 and 102 bps

Table 2
Max effective spread return premium.
The table reports various measures of next-month returns (and alphas) across portfolios sorted by MTAQ maximum effective spreads in month t-1 for the period 2004 to 2013. Panel A reports mean returns, mean excess returns, and mean adjusted return in month t. Excess returns are returns in excess of the risk-free rate, which is approximated with one-month U.S. Government T-bill yields. Adjusted returns are the returns for each stock in excess of the CRSP market index. We report mean returns across each portfolio. Column (6) presents the difference between extreme portfolios along with a corresponding t-statistic (in parentheses). Panels B and C report the estimated intercept (alpha) from the different variants of the following equation.

$$Excess\ Return_{i,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t^j + \varepsilon_{i,t}.$$

The dependent variable is excess return for stock i in month t. The independent variables include the market risk premium (*MRP*), the small-minus-big risk factor (*SMB*), the high-minus-low risk factor (*HML*), the Carhart (1997) up-minus-down risk factor (*UMD*), and Pastor-Stambaugh liquidity risk factor (*LIQ*). Panel B provides the results of a single-factor, a three-factor, and a four-factor model. *CAPM Alpha* is the intercept from estimating a trading CAPM. *FF3F Alpha* is the intercept from estimating the above equation but excluding *UMD* and *LIQ*. *FF4F Alpha* is the estimated intercept from the above equation without including *LIQ*. Panel C provides the results from estimating a five-factor model using different liquidity risk factors from Pastor and Stambaugh (2003). 5F *Alpha* is the intercept from estimating the full version of the above equation. The variants of the liquidity risk factors – *LEVEL*, *INNOV*, and *VWF* – are described in Pastor and Stambaugh (2003). As before, we report these alphas across portfolios sorted by max spreads along with differences between extreme portfolios with corresponding t-statistics in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. Monthly returns						
	QI	QII	QIII	QIV	QV	QV-QI
	(1)	(2)	(3)	(4)	(5)	(6)
Monthly Returns	0.0092	0.0094	0.0097	0.0114	0.0202	0.0110***
						(3.47)
Excess Returns	0.0079	0.0082	0.0085	0.0101	0.0189	0.0110***
						(3.47)
Adj. Returns	0.0018	0.0021	0.0024	0.0041	0.0128	0.0110***
						(3.47)
Panel B. CAPM and three-factor and four-factor regressions						
CAPM Alphas	0.0015	0.0007	0.0005	0.0020	0.0111***	0.0096***
	(1.58)	(0.56)	(0.31)	(1.04)	(3.61)	(3.41)
FF3F Alphas	0.0013*	0.0004	0.0002	0.0017	0.0108***	0.0094***
	(1.85)	(0.61)	(0.22)	(1.29)	(4.02)	(3.53)
FF4F Alphas	0.0014*	0.0006	0.0005	0.0022*	0.0116***	0.0102***
	(1.91)	(0.98)	(0.69)	(1.95)	(4.92)	(4.24)
Panel C. Five-factor regressions						
5F *LEVEL Alphas*	0.0014*	0.0008	0.0007	0.0023**	0.0119***	0.0105***
	(1.73)	(1.14)	(0.82)	(1.99)	(5.14)	(4.42)
5F *INNOV Alphas*	0.0014*	0.0006	0.0005	0.0022*	0.0116***	0.0102***
	(1.93)	(0.98)	(0.68)	(1.96)	(4.91)	(4.23)
5F VWF *Alphas*	0.0010	0.0003	0.0002	0.0020*	0.0116***	0.0106***
	(1.50)	(0.53)	(0.28)	(1.81)	(4.89)	(4.39)

Table 3
Max price impact return premium.
The table reports various measures of next-month returns (and alphas) across portfolios sorted by MTAQ maximum 5-min price impact in month *t*-1 for the period 2004 to 2013. Panel A reports mean returns, mean excess returns, and mean adjusted return in month *t*. Excess returns are returns in excess of the risk free rate, which is approximated with one-month U.S. Government T-Bill yields. Adjusted returns are the returns for each stock in excess of the CRSP market index. We report mean returns across each portfolio. Column [6] presents the difference between extreme portfolios along with a corresponding t-statistic (in parentheses). Panels B and C reports the estimated intercept (alpha) from the different variants of the following equation.

$$Excess\ Return_{i,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t^j + \varepsilon_{i,t}$$

The dependent variable is excess return for stock *i* in month *t*. The independent variables include the market risk premium (*MRP*), the small-minus-big risk factor (*SMB*), the high-minus-low risk factor (*HML*), the Carhart (1997) up-minus-down risk factor (*UMD*), and Pastor-Stambaugh liquidity risk factor (*LIQ*). Panel B provides the results of a single-factor, a three-factor, and a four-factor model. *CAPM Alpha* is the intercept from estimating a trading CAPM. *FF3F Alpha* is the intercept from estimating the above equation but excluding *UMD* and *LIQ*. *FF4F Alpha* is the estimated intercept from the above equation without including *LIQ*. Panel C provides the results from estimating a five-factor model using different liquidity risk factors from Pástor and Stambaugh (2003). *5F Alpha* is the intercept from estimating the full version of the above equation. The variants of the liquidity risk factors – *LEVEL*, *INNOV*, and *VWF* – are described in Pástor and Stambaugh (2003). As before, we report these alphas across portfolios sorted by max spreads along with differences between extreme portfolios with corresponding *t*-statistics in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. Monthly returns	QI	QII	QIII	QIV	QV	QV-QI
	(1)	(2)	(3)	(4)	(5)	(6)
Monthly Returns	0.0089	0.0094	0.0101	0.0123	0.0193	0.0105***
						(3.18)
Excess Returns	0.0076	0.0081	0.0088	0.0110	0.0181	0.0105***
						(3.18)
Adj. Returns	0.0015	0.0020	0.0027	0.0049	0.0120	0.0105***
						(3.18)
Panel B. CAPM and three-factor and four-factor regressions						
CAPM Alphas	0.0015*	0.0007	0.0007	0.0027	0.0100***	0.0085***
	(1.90)	(0.58)	(0.43)	(1.29)	(3.36)	(2.99)
FF3F Alphas	0.0014*	0.0005	0.0004	0.0024	0.0097***	0.0083***
	(1.97)	(0.68)	(0.42)	(1.58)	(3.80)	(3.20)
FF4F Alphas	0.0015**	0.0006	0.0007	0.0030**	0.0105***	0.0091***
	(2.03)	(0.93)	(0.87)	(2.30)	(4.80)	(3.97)
Panel C. Five-factor regressions						
5F *LEVEL Alphas*	0.0017**	0.0007	0.0007	0.0031**	0.0108***	0.0091***
	(2.31)	(0.92)	(0.82)	(2.50)	(4.92)	(3.97)
5F *INNOV Alphas*	0.0015**	0.0006	0.0007	0.0029**	0.0106***	0.0091***
	(2.04)	(0.93)	(0.87)	(2.30)	(4.79)	(3.97)
5F VWF *Alphas*	0.0011*	0.0002	0.0004	0.0027**	0.0106***	0.0095***
	(1.66)	(0.41)	(0.51)	(2.14)	(4.81)	(4.15)

per month, respectively. In Panel C of Table 2, we find that the differences in 5F alphas between extreme portfolios range from 102 to 106 bps, depending on the Pástor and Stambaugh (2003) liquidity risk factor used. These results suggest that, after controlling for common risk factors, we continue to find a significant return premium associated with max spreads. Therefore, stocks with higher max spreads tend to outperform, on a risk-adjusted basis, stocks with lower max spreads.[7]

3.2. Portfolio analysis: max price impact return premium

As a measure of robustness to our analysis using effective spreads, in this subsection we examine the return premium associated with max price impacts. Similar to before, we analyze various measures of returns (and alphas) in month *t* across portfolios sorted into quintiles by max price impacts in month *t*-1. Panel A of Table 3 displays average returns, average excess returns, and average adjusted returns in month *t*. We find a monotonic increase in mean returns across max price impact quintiles. For instance, we show that the average raw return in QI is 89 bps per month, which increases to 193 bps per month in QV. Similar results are reported for excess returns and adjusted returns. The difference in returns between extreme portfolios is 105 bps per month, which is significant at the 0.01 level and is economically meaningful.

Panels B and C of Table 3 report the estimated intercepts (alphas) from equation (3) on max price impact portfolios. Although non-monotonic, we find that the average alphas generally increase across these portfolios. For instance, Panel B shows that the average alphas in QV range from 97 to 105 bps per month, compared to 14 to 15 bps in QI. We find the 83 to 91 bps differences between extreme price impact portfolios are significant at the 0.01 level. We draw similar conclusions in Panel C, where we present estimates of 5F alphas. In fact, the differences between extreme portfolios are 91–95 bps per month. Our

[7] We do not find that the results in Table 2 are driven by outliers in max spreads. For instance, eliminating observations at the 1st and 99th percentiles does not meaningfully change our conclusions. We also find that our results are strengthened if we remove stocks with prices less than $5.

Table 4
Double-sorted portfolios on max effective spreads and size.
The table reports current-month excess returns (and alphas) across portfolios double sorted by MTAQ maximum effective spreads and market capitalization in month *t*-1. Excess returns are returns in excess of the risk-free rate, which is approximated with one-month U.S. Government T-bill yields. We report the estimated intercept (alpha) from the following capital asset pricing model:

$$Excess\ Return_{i,t} = \alpha + \beta_1 MRP_t + \varepsilon_{i,t}.$$

The dependent variable is excess return for stock *i* in month *t* and the independent variable is the market risk premium (*MRP*). *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

		Size Quintiles					
		QI	QII	QIII	QIV	QV	QV-Q1
		(1)	(2)	(3)	(4)	(5)	(6)
Max Effective Spread Quintiles	QI	0.0019	0.0021	0.0006	0.0006	0.0020**	0.0001
		(1.14)	(1.39)	(0.48)	(0.67)	(2.37)	(0.07)
	QII	0.0018	−0.0007	0.0008	0.0005	0.0010	−0.0008
		(0.90)	(-0.40)	(0.47)	(0.36)	(0.89)	(-0.36)
	QIII	0.0010	−0.0004	−0.0002	0.0004	0.0016	0.0005
		(0.45)	(-0.16)	(-0.07)	(0.24)	(1.15)	(0.19)
	QIV	0.0094***	0.0020	−0.0004	−0.0015	0.0006	−0.0088***
		(3.32)	(0.87)	(-0.14)	(-0.59)	(0.29)	(-2.58)
	QV	0.0339***	0.0137***	0.0024	0.0038	0.0017	−0.0322***
		(6.69)	(3.37)	(0.75)	(1.26)	(0.64)	(-5.64)
	QV-QI	0.0320***	0.0115***	0.0018	0.0031	−0.0003	
		(6.02)	(2.66)	(0.53)	(0.99)	(-0.11)	

results suggest that, after controlling for common risk factors, that there is still a significant return premium associated with max price impacts.

As another robustness check, we replicate our analysis using double-sorted portfolios. In particular, we estimate equation (3) for double-sorted portfolios that are first sorted into size quintiles and then, within each size quintile, we sort stocks into max spread quintiles. For brevity, we only report CAPM alphas for the double-sorted portfolios, but similar results are found when we estimate other variants of equation (3).

Table 4 reports the results. A few results are noteworthy. First, at the bottom of each column, we report the alphas for differences across extreme portfolios. The QV-Q1 differences generally decrease across columns and are only significant in columns (1) and (2). These results imply that the max spread return premia is driven by smaller-cap stocks. Second, we find that in column (6), the high-minus-low difference across market cap portfolios generally decrease across rows. In particular, only in max spread portfolios IV and V are the differences negative and statistically significant. These findings imply that the negative size premium is driven by stocks with the highest max spread. Stated differently, the findings in Table 4 indicate that the return premium associated with max spreads is driven by market cap.

3.3. Fama-MacBeth regressions: max spreads

In the following subsection, we examine whether cross-sectional relations between future returns and max spreads exist after controlling for a variety of firm-specific variables in a Fama and Macbeth (1973) regression framework. In other words, we want to examine whether max spreads and max price impacts predict future returns better than other measures of liquidity. We estimate the following model using pooled stock-month observations:

$$\begin{aligned} Return_{i,t} = {} & \beta_0 + \beta_1 MaxESpread_{i,t-1} + \beta_2 ESpread_{i,t-1} + \beta_3 Amihud_{i,t-1} + \beta_4 Turn_{i,t-1} + \beta_5 \ln(Size_{i,t-1}) + \beta_6 \ln(B/M_{i,t-1}) \\ & + \beta_7 Beta_{i,t-1} + \beta_8 IdioVolt_{i,t-1} + \beta_9 MOM_{i,t-1} + \varepsilon_{i,t}\ , \end{aligned} \tag{4}$$

where the dependent variable is the raw return for stock *i* in month *t*. The independent variables are measured in month *t*-1. We note that when estimating equation (4) using a Fama and Macbeth (1973) approach, we report average coefficients and *t*-statistics obtained from Newey and West (1987) standard errors that account for three lags. For ease of interpretation, we standardize all independent variables in each period by the cross-sectional standard deviation.

We report the results of estimating equation (4) in Table 5. The control variables display their expected signs.[8] Column (1) presents the simple regression results with *MaxESpread* as the explanatory variable of interest. We find that a one standard deviation increase in *MaxESpread* is associated with an 18 bps increase in next-month returns. Thus, after controlling for firm-

[8] Banz (1981) shows that market cap affects future returns. Similar results are found in Fama and French (1992), who also show that book-to-market ratios are important predictors of future returns. Ang et al. (2006, 2009) show that volatility explains the cross-section of expected returns while Jegadeesh and Titman (1993) discuss the return premium associated with return momentum.

Table 5
Fama-MacBeth regressions: Max effective spreads.
The table reports the results from estimating the following equation using pooled stock-month observations.

$$Return_{i,t} = \beta_0 + \beta_1 MaxESpread_{i,t-1} + \beta_2 ESpread_{i,t-1} + \beta_3 Amihud_{i,t-1} + \beta_4 Turn_{i,t-1} + \beta_5 \ln(Size_{i,t-1}) + \beta_6 \ln(B/M_{i,t-1}) + \beta_7 Beta_{i,t-1} + \beta_8 IdioVolt_{i,t-1} + \beta_9 MOM_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the raw return for stock *i* in month *t*. The independent variables, which are measured in month *t*-1 and standardized each month by the cross-sectional standard deviation, include the following: *MaxESpread* is the maximum intraday MTAQ percentage effective spread during a particular month. *ESpread* is the percentage effective spread. *Amihud* is average of Amihud's (2002) price impact, which is the ratio of the absolute value of daily returns scaled by daily dollar volume. *Turn* is the share turnover of the average daily volume scaled by shares outstanding (in percent). Ln*(Size)* is the natural log of market capitalization on the last day of each month. Ln*(B/M)* is the natural log of the book-to-market ratio. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *IdioVolt* is the standard deviation of daily residual returns over a rolling six-month period, where the residual returns are obtained from a daily Fama and French (1996) and Carhart (1997) four-factor model. *Mom* is the cumulative return for stock *i* during month *t*-12 to *t*-2. We estimate the above equation using a Fama and Macbeth (1973) approach and report average coefficients and *t*-statistics obtained from Newey and West (1987) standard errors that account for three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	0.0405***	0.0387**	0.0392***	0.0405**
	(2.93)	(2.28)	(2.80)	(2.38)
$MaxESpread_{i,t\text{-}1}$	0.0018***	0.0020***	0.0017***	0.0021***
	(3.08)	(2.85)	(2.97)	(3.01)
$ESpread_{i,t\text{-}1}$		−0.0005		−0.0012
		(-0.32)		(-0.78)
$Amihud_{i,t\text{-}1}$			0.0006	0.0017**
			(0.55)	(2.22)
$Turn_{i,t\text{-}1}$	−0.0012	−0.0011	−0.0011	−0.0011
	(-1.31)	(-1.37)	(-1.22)	(-1.35)
$Size_{i,t\text{-}1}$	−0.0013	−0.0012	−0.0012	−0.0013
	(-1.19)	(-0.83)	(-1.08)	(-0.94)
$B/M_{i,t\text{-}1}$	0.0046***	0.0046***	0.0046***	0.0046***
	(6.53)	(6.42)	(6.44)	(6.39)
$Beta_{i,t\text{-}1}$	0.0006	0.0003	0.0007	0.0003
	(0.49)	(0.25)	(0.50)	(0.22)
$IdioVolt_{i,t\text{-}1}$	−0.0016	−0.0013	−0.0017*	−0.0014
	(-1.54)	(-1.11)	(-1.71)	(-1.24)
$Mom_{i,t\text{-}1}$	0.0004	0.0004	0.0005	0.0005
	(0.24)	(0.26)	(0.28)	(0.27)

specific factors, we find that max spreads predict positive and significant returns. We also include average intraday percent effective spread as a control variable in equation (4) and report the results in column (2). After controlling for mean spreads, we find that a one standard deviation increase in *MaxESpread* is associated with a 20 bps increase in next-month returns. To control for the price impact of trading volume at the daily level, we include Amihud's (2002) illiquidity measure in equation (4) and report the results in column (3). Even after controlling for illiquidity, we continue to find a positive and significant beta coefficient on *MaxESpread*. The full model specification results are reported in column (4). They show that a one standard deviation increase in *MaxESpread* is associated with a 21 bps increase in next-month returns, other factors held constant. If we assume that illiquidity is inherently risky and that less liquid stocks should be associated with a return premium, then our results in Table 5 seem to indicate that max spreads might be a better proxy for illiquidity than mean spreads.

We recognize the possibility that the conclusions we draw might be adversely affected by the presence of multicollinearity, given the strong correlation between max spreads and mean spreads. In unreported tests, we estimate a pooled OLS regression replicating the specification in for column (4) of Table 5 and find that variance inflation factors are 1.14 for the coefficient on *MaxESpread* and 1.52 for the coefficient on *ESpread*. The small size of these factors suggests that multicollinearity bias is not an issue.

As another attempt at documenting the return premium associated with max spreads, we plot the monthly standardized cross-sectional coefficients from Fama and Macbeth (1973) regressions of MaxESpread on future returns in Fig. 2. Here, we see that most of the monthly coefficients are positive. We also find some evidence that the max spread return premium was highest during the recent financial crisis, but declined marginally over the sample period.

3.4. Fama-MacBeth regressions: max price impact

Next, we analyze the cross-sectional relations between future returns and max price impacts in a controlled Fama and Macbeth (1973) regression framework. We estimate the following model using pooled stock-month observations:

$$Return_{i,t} = \beta_0 + \beta_1 MaxPrcImpact_{i,t-1} + \beta_2 PrcImpact_{i,t-1} + \beta_3 Amihud_{i,t-1} + \beta_4 Turn_{i,t-1} + \beta_5 \ln(Size_{i,t-1}) + \beta_6 \ln(B/M_{i,t-1}) + \beta_7 Beta_{i,t-1} + \beta_8 IdioVolt_{i,t-1} + \beta_9 MOM_{i,t-1} + \varepsilon_{i,t}\ , \tag{5}$$

Table 6
Fama-MacBeth regressions – Max price impact.
The table reports the results from estimating the following equation using pooled stock-month observations.

$$Return_{i,t} = \beta_0 + \beta_1 MaxPrcImpact_{i,t-1} + \beta_2 PrcImpact_{i,t-1} + \beta_3 Amihud_{i,t-1} + \beta_4 Turn_{i,t-1} + \beta_5 \ln(Size_{i,t-1}) + \beta_6 \ln(B/M_{i,t-1}) + \beta_7 Beta_{i,t-1} + \beta_8 IdioVolt_{i,t-1} + \beta_9 MOM_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the raw return for stock *i* in month *t*. The independent variables, which are measured in month *t*-1 and standardized each month by the cross-sectional standard deviation, include the following: *MaxPrcImpact* is the maximum intraday MTAQ percentage price impact during a particular month. *PrcImpact* is the 5-min percentage price impact. *Amihud* is average of Amihud's (2002) price impact, which is the ratio of the absolute value of daily returns scaled by daily dollar volume. *Turn* is the share turnover of the average daily volume scaled by shares outstanding (in percent). Ln*(Size)* is the natural log of market capitalization on the last day of each month. Ln*(B/M)* is the natural log of the book-to-market ratio. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *IdioVolt* is the standard deviation of daily residual returns over a rolling six-month period, where the residual returns are obtained from a daily Fama and French (1996) and Carhart (1997) four-factor model. *Mom* is the cumulative return for stock *i* during month *t*-12 to *t*-2. We estimate the above equation using a Fama and Macbeth (1973) approach and report average coefficients and *t*-statistics obtained from Newey and West (1987) standard errors that account for three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	0.0428***	0.0428***	0.0414***	0.0417***
	(3.04)	(2.87)	(2.91)	(2.80)
$MaxPrcImpact_{i,t\text{-}1}$	0.0011***	0.0011**	0.0011***	0.0011**
	(3.04)	(2.32)	(2.93)	(2.39)
$PrcImpact_{i,t\text{-}1}$		−0.0002		−0.0003
		(-0.37)		(-0.54)
$Amihud_{i,t\text{-}1}$			0.0007	0.0008
			(0.65)	(0.81)
$Turn_{i,t\text{-}1}$	−0.0013	−0.0013	−0.0012	−0.0012
	(-1.39)	(-1.43)	(-1.30)	(-1.34)
$Size_{i,t\text{-}1}$	−0.0015	−0.0015	−0.0014	−0.0014
	(-1.36)	(-1.26)	(-1.23)	(-1.19)
$B/M_{i,t\text{-}1}$	0.0046***	0.0046***	0.0046***	0.0046***
	(6.54)	(6.51)	(6.45)	(6.43)
$Beta_{i,t\text{-}1}$	0.0006	0.0006	0.0006	0.0006
	(0.48)	(0.44)	(0.50)	(0.46)
$IdioVolt_{i,t\text{-}1}$	−0.0013	−0.0013	−0.0015	−0.0015
	(-1.30)	(-1.27)	(-1.48)	(-1.45)
$Mom_{i,t\text{-}1}$	0.0004	0.0004	0.0005	0.0004
	(0.23)	(0.23)	(0.27)	(0.26)

where the dependent variable is the raw return for stock *i* in month *t*. The independent variables are measured in month *t*-1. We estimate equation (5) using a Fama and Macbeth (1973) approach, and report average coefficients and *t*-statistics obtained from Newey and West (1987) standard errors in Table 6. Again, all independent variables in each period are standardized by the cross-sectional standard deviation.

In column (1) of Table 6, we find that a one standard deviation increase in the max price impact is associated with an 11 bps increase in next-month returns, other firm factors held constant. Column (2) shows a similar result, while controlling for the mean price impact. In fact, the coefficient on *MaxPrcImpact* remains at 0.0011, indicating that a standard deviation increase in the max price impact is associated with an 11 bps increase in next-month returns. We draw identical conclusions in the full model specification reported in column (4). Similar to the previous subsection, we estimate a pooled OLS regression replicating the specification in column (4) of Table 5 and find that variance inflation factors are 1.23 for the coefficient on *MaxPrcImpact* and 1.35 for the coefficient on *PrcImpact*, providing no indication of multicollinearity bias. We interpret these results as an indication that the max price impact could be a better proxy for expected illiquidity than the mean price impact.

3.5. Robustness tests: extended CRSP sample

To this point, we have shown that max spreads and max price impact command significant return premiums. However, our MTAQ sample period is limited to January of 2004 to December of 2013, which only gives 119 monthly observations in our portfolio tests. To provide some additional robustness, we present results on closing spreads calculated from the much smaller CRSP daily files. Doing so allows us to extend our sample time period from January 1993 to December 2017. This extension provides 299 monthly observations in our portfolio tests.[9]

From CRSP, we obtain the universe of stocks from 1993 to 2017 and merge these data with Compustat data. We then calculate bid-ask spreads according to Chung and Zhang (2014) as follows:

[9] While we would prefer to use historical data that extends before 1993, the CRSP closing ask and bid prices, which were recently added, are not reliably available for every stock.

$$Percent\ Closing\ Spread_{i,t} = \frac{(Ask_{i,t} - Bid_{i,t})}{M_{i,t}}. \quad (6)$$

where $Ask_{i,t}$ is the closing ask price for stock *i* on day *t*, $Bid_{i,t}$ is the closing bid price for stock *i* on day *t*, and $M_{i,t}$ is the midpoint between the closing ask and bid prices. We then identify the maximum daily closing spread for a particular stock in a particular month. The extended CRSP sample consists of 15,415 unique securities and 1.56 million stock-month observations.

Table 7 reports the summary statistics that describe the extended CRSP sample. *MaxCSpread* is the maximum daily closing percent bid-ask spread during a particular month. *CSpread* is the daily closing percent bid-ask spread averaged across each month. The average stock in the sample has a maximum closing spread of 5.12% and a mean CRSP spread of 2.82%, indicating large variation in closing spreads. We also show that the average stock has a market capitalization of $2.74 billion, daily share turnover of 0.73%, Amihud illiquidity of 4.942, a book-to-market ratio of 0.524, and idiosyncratic volatility of 2.92%.

To examine how well CRSP closing bid-ask spreads approximate intraday MTAQ effective spreads, we estimate simple correlations. Both Roll and Subrahmanyam (2010) and Chung and Zhang (2014) find that closing bid-ask spreads in CRSP provide a close approximation of intraday effective spreads. Table 8 provides correlation matrices across various CRSP and MTAQ liquidity measures. Panel A of Table 8 presents pooled correlations, and Panel B reports cross-sectional correlations. We find that the pooled correlation coefficient between *ESpread* and *CSpread* is 0.8820, suggesting that MTAQ effective spreads are 88.20% correlated with CRSP closing spreads. In our cross-sectional correlation, we show that MTAQ effective spreads are 96.26% correlated with CRSP closing spreads. This is similar to the finding in Chung and Zhang (2014).

Interestingly, we find that the pooled (cross-sectional) correlation coefficient between *MaxESpread* and *ESpread* is only 0.3650 (0.6594), suggesting that max spreads capture something other than mean spreads. The pooled and cross-sectional correlations between the max price impact and the mean price impact are 33.11% and 60.44%, respectively. These results provide further support for our claim that max spreads and max price impacts are different (better) proxies for illiquidity than mean spreads and mean price impacts. Max spreads and max CRSP spreads have a correlation of 0.6018 in the cross-section. We also note that max CRSP spreads and mean CRSP spreads are highly correlated (82.98%) in pooled tests.

Somewhat unexpectedly, we find that Amihud illiquidity, which is often used as a low-frequency proxy for price impact, is only 5.31% correlated with the intraday percent price impact in pooled tests and 36.68% correlated in cross-sectional tests. Amihud illiquidity has a much stronger cross-sectional correlation with percent effective spreads (59.79%) than with the intraday percent price impact.

As an additional way to provide some description of the data we use, we report mean CRSP spreads and max CRSP spreads, averaged across each year in sample time period. The results are reported in Fig. 1. According to the figure, we find that both mean CRSP spreads and max CRSP spreads decrease across time, except during the recent financial crisis. This decline is primarily due to the decimalization of security prices. However, the decline in both mean and max CRSP spreads has not been systematic. It appears that max CRSP spreads decline at a slower pace than mean CRSP spreads.

We next examine whether there is a return premium associated with the max CRSP spreads obtained from CRSP, similar to the return premium of the MTAQ percent effective spreads. First we examine this relation in a traditional portfolio framework. Again, we analyze various measures of returns (and alphas) in month *t* across portfolios sorted into quintiles by maximum closing spreads in month *t*-1. Table 9 reports the results. Panel A shows average returns, average excess returns, and average adjusted returns in month *t*. We find a non-monotonic increase in mean returns across maximum closing spread quintiles. For instance, we show that the average raw return in QI is 94 bps per month, which increases to 103 bps per month in QII, decreases to 102 and 100 bps per month in QIII and QV, and increases to 160 bps per month in QV. Similar results are reported

Table 7
Summary statistics for extended CRSP sample (1993–2017).
The table describes the security characteristics in the CRSP sample. The analysis covers the period from January of 1993 to December of 2017. *MaxCSpread* is the maximum daily (closing) percentage bid-ask spread during a particular month. *CSpread* is the percentage bid-ask spread. *Amihud* is the measure of price impact from Amihud (2002), which is the scaled ratio of the absolute value of daily returns to daily dollar volume. *Turn* is the share turnover of the average daily volume scaled by shares outstanding (in percent). Size is the market capitalization on the last day of each month. *B/M* is the book-to-market ratio. *IdioVolt* is the standard deviation of daily residual returns over a rolling six-month period, where residual returns are obtained from estimating a daily Fama and French (1996) and Carhart (1997) four-factor model. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period.

	Mean	Std. Dev.	Median	25th Percentile	75th Percentile
	(1)	(2)	(3)	(4)	(5)
MaxCSpread	0.0512	0.0866	0.0246	0.0058	0.0619
CSpread	0.0282	0.0529	0.0117	0.0022	0.0331
Amihud	4.9420	108.7716	0.0376	0.0028	0.5772
Turn	0.0073	0.1060	0.0036	0.0015	0.0079
Size ($ billions)	2.7427	14.3554	0.2133	0.0487	1.0268
B/M	0.5237	47.8436	0.0596	0.0323	0.1003
IdioVolt	0.0292	0.0292	0.0211	0.0128	0.0357
Beta	0.7708	2.6375	0.7351	0.1294	1.3863

Table 8
Correlation matrices (MTAQ and CRSP samples).
The table reports correlation matrices for the liquidity measures used for the merged CRSP and MTAQ samples. Panel A reports pooled correlations, while Panel B reports cross-sectional correlations. *MaxCSpread* is the maximum daily closing spread during a particular month. *CSpread* is the average daily closing spread. *MaxESpread* is the maximum intraday effective spread during a particular month. *ESpread* is the average intraday percentage effective spread. *MaxPrcImpact* is the maximum intraday price impact during a particular month. *PrcImpact* is the average intraday price impact. *Amihud* is the measure of price impact from Amihud (2002), which is the scaled ratio of the absolute value of daily returns to daily dollar volume. *SpreadSkew* is the skewness of the CRSP closing spreads during a particular month. *ESpreadSkew* is the skewness of the MTAQ intraday effective spreads measured in 30-min time intervals during a particular month.

Panel A. MTAQ/CRSP pooled correlations

	Max CSpread	*CSpread*	*Max ESpread*	*ESpread*	*MaxPrc Impact*	*PrcImpact*	*Amihud*	*Spread Skew*	*ESpread Skew*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MaxCSpread	1.0000	0.8298	0.2054	0.6987	0.2102	0.1874	0.2331	0.1150	−0.1267
CSpread		1.0000	0.2240	0.8820	0.2408	0.2322	0.2876	−0.0378	−0.1770
MaxESpread			1.0000	0.3650	0.3790	0.1052	0.0657	0.0064	0.1481
ESpread				1.0000	0.2824	0.2480	0.2873	−0.0594	−0.1666
MaxPrcImpact					1.0000	0.3311	0.0621	−0.0010	0.0420
PrcImpact						1.0000	0.0531	−0.0178	−0.0428
Amihud							1.0000	−0.0113	−0.0388
SpreadSkew								1.0000	0.0683
ESpreadSkew									1.0000

Panel B. MTAQ/CRSP cross-sectional correlations

	Max CSpread	*CSpread*	*Max ESpread*	*ESpread*	*MaxPrc Impact*	*PrcImpact*	*Amihud*	*Spread Skew*	*ESpread Skew*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MaxCSpread	1.0000	0.9666	0.6018	0.9419	0.6036	0.6833	0.6078	−0.0948	−0.4963
CSpread		1.0000	0.5986	0.9626	0.6012	0.7028	0.5948	−0.1702	−0.5247
MaxESpread			1.0000	0.6594	0.7949	0.5542	0.3458	−0.0940	−0.1048
ESpread				1.0000	0.6514	0.7416	0.5979	−0.1713	−0.5267
MaxPrcImpact					1.0000	0.6044	0.3471	−0.1003	−0.2151
PrcImpact						1.0000	0.3668	−0.1650	−0.3950
Amihud							1.0000	−0.0470	−0.2505
SpreadSkew								1.0000	0.1737
ESpreadSkew									1.0000

for excess returns and adjusted returns. The difference in returns between extreme portfolios is 67 bps per month, which is significant at the 0.01 level.

Panels B and C of Table 9 report the estimated intercepts (alphas) from equation (3) on max CRSP spread portfolios. We find that the only significant alphas are in the largest max CRSP spread quintile, which range from 71 bps to 118 bps per month depending on the risk model. The differences between extreme portfolios are both statistically significant and economically meaningful, as they range from 71 bps per month to 118 bps per month. Our results indicate that after controlling for common risk factors, there is a significant return premium associated with max CRSP spreads.

Next, we analyze if there is a significant cross-sectional relation between max CRSP spreads and future returns. We estimate the following model using pooled stock-month observations:

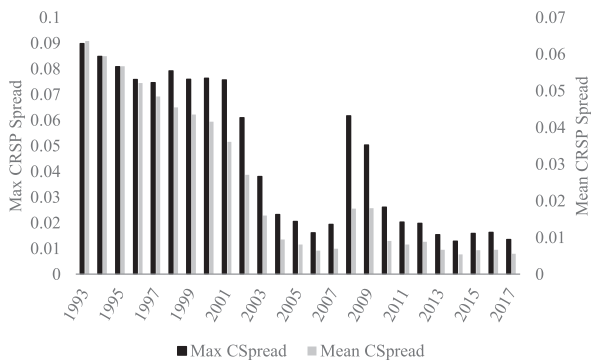

Fig. 1. Maximum and mean CRSP closing spreads.
The figure shows average maximum daily closing spreads and average percentage closing spreads during the sample time period 1993 to 2017.

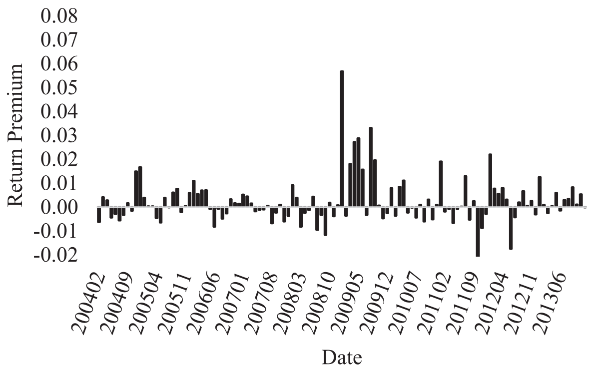

Fig. 2. Maximum effective spread return premium.
The figure shows standardized Fama and Macbeth (1973) regression coefficients on max bid ask effective spreads for each month in our TAQ sample time period. The variable max effective spread is standardized each month by its cross-sectional standard deviation and then regressed on future raw returns.

Table 9
Max CRSP spread return premium.
The table reports various measures of next-month returns (and alphas) across portfolios sorted by CRSP maximum closing bid-ask spreads in month t-1. Panel A reports mean returns, mean excess returns, and mean adjusted return in month t. Excess returns are returns in excess of the risk-free rate, which is approximated with one-month U.S. Government T-bill yields. Adjusted returns are the returns for each stock in excess of the CRSP market index. We report mean returns across each portfolio. Column [6] presents the difference between extreme portfolios along with a corresponding t-statistic (in parentheses). Panels B and C reports the estimated intercept (alpha) from the different variants of the following equation:

$$Excess\ Return_{i,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t^j + \varepsilon_{i,t}.$$

The dependent variable is excess return for stock i in month t. The independent variables include the market risk premium (*MRP*), the small-minus-big risk factor (*SMB*), the high-minus-low risk factor (*HML*), the Carhart (1997) up-minus-down risk factor (*UMD*), and Pastor-Stambaugh liquidity risk factor (*LIQ*). Panel B provides the results of a single-factor, a three-factor, and a four-factor model. *CAPM Alpha* is the intercept from estimating a trading CAPM. *FF3F Alpha* is the intercept from estimating the above equation but excluding *UMD* and *LIQ*. *FF4F Alpha* is the estimated intercept from the above equation without including *LIQ*. Panel C provides the results from estimating a five-factor model using different liquidity risk factors from Pastor and Stambaugh (2003). 5F *Alpha* is the intercept from estimating the full version of the above equation. The variants of the liquidity risk factors – *LEVEL*, *INNOV*, and *VWF* – are described in Pastor and Stambaugh (2003). As before, we report these alphas across portfolios sorted by max CRSP spreads along with differences between extreme portfolios with corresponding t-statistics in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. Monthly returns	QI	QII	QIII	QIV	QV	QV-QI
	(1)	(2)	(3)	(4)	(5)	(6)
Monthly Returns	0.0094	0.0103	0.0102	0.0100	0.0160	0.0067**
						(2.32)
Excess Returns	0.0074	0.0083	0.0082	0.0080	0.0140	0.0067**
						(2.32)
Adj. Returns	0.0006	0.0016	0.0015	0.0013	0.0073	0.0067**
						(2.32)
Panel B. CAPM and three-factor and four-factor regressions						
CAPM Alphas	−0.0001	0.0005	0.0003	0.0002	0.0071**	0.0072**
	(-0.12)	(0.41)	(0.17)	(0.11)	(2.34)	(2.60)
FF3F Alphas	−0.0002	−0.0003	−0.0010	−0.0008	0.0069**	0.0071**
	(-0.39)	(-0.51)	(-1.02)	(-0.45)	(2.47)	(2.56)
FF4F Alphas	−0.0001	0.0006	0.0008	0.0021	0.0105***	0.0105***
	(-0.12)	(1.02)	(0.91)	(1.24)	(3.55)	(3.59)
Panel C. Five-factor regressions						
5F *LEVEL Alphas*	0.0003	0.0009	0.0010	0.0026	0.0118***	0.0118***
	(0.05)	(1.40)	(1.17)	(1.50)	(3.81)	(3.78)
5F *INNOV Alphas*	−0.0002	0.0007	0.0011	0.0024	0.0109***	0.0111***
	(-0.33)	(1.04)	(1.27)	(1.33)	(3.43)	(3.50)
5F VWF *Alphas*	−0.0004	0.0004	0.0010	0.0021	0.0105***	0.0109***
	(-0.64)	(0.71)	(1.10)	(1.24)	(3.44)	(3.53)

$$Return_{i,t} = \beta_0 + \beta_1 MaxCSpread_{i,t-1} + \beta_2 CSpread_{i,t-1} + \beta_3 Amihud_{i,t-1} + \beta_4 Turn_{i,t-1} + \beta_5 \ln(Size_{i,t-1}) + \beta_6 \ln(B/M_{i,t-1}) + \beta_7 Beta_{i,t-1} + \beta_8 IdioVolt_{i,t-1} + \beta_9 MOM_{i,t-1} + \varepsilon_{i,t}\ , \quad (7)$$

Table 10
Fama-MacBeth regressions: Max CRSP spreads.
The table reports the results from estimating the following equation using pooled stock-month observations.The dependent variable is the raw return for stock *i* in month *t*. The independent variables, which are measured in month *t*-1 and standardized each month by the cross-sectional standard deviation, including the following: *MaxCSpread* is the maximum daily closing percentage bid-ask spread during a particular month. *CSpread* is the percentage closing bid-ask spread. *Amihud* is average of Amihud's (2002) price impact, which is the ratio of the absolute value of daily returns scaled by daily dollar volume. *Turn* is the share turnover of the average daily volume scaled by shares outstanding (in percent). Ln*(Size)* is the natural log of market capitalization on the last day of each month. Ln*(B/M)* is the natural log of the book-to-market ratio. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *IdioVolt* is the standard deviation of daily residual returns over a rolling six-month period, where the residual returns are obtained from a daily Fama and French (1996) and Carhart (1997) four-factor model. *Mom* is the cumulative return for stock *i* during month *t*-12 to *t*-2. We estimate the above equation using a Fama and Macbeth (1973) approach and report average coefficients and *t*-statistics obtained from Newey and West (1987) standard errors that account for three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	0.0358***	0.0340***	0.0390***	0.0378***
	(4.04)	(3.70)	(4.44)	(4.14)
$MaxCSpread_{i,t\text{-}1}$	0.0038***	0.0046***	0.0028***	0.0046***
	(4.77)	(3.57)	(3.67)	(3.36)
$CSpread_{i,t\text{-}1}$		−0.0006		−0.0018
		(-0.58)		-(1.53)
$Amihud_{i,t\text{-}1}$			0.0035***	0.0036***
			(5.33)	(5.35)
$Turn_{i,t\ \text{-}1}$	−0.0013**	−0.0013**	−0.0012**	−0.0012**
	(-2.50)	(-2.47)	(-2.18)	(-2.19)
$Size_{i,t\text{-}1}$	−0.0002	−0.0001	−0.0006	−0.0004
	(-0.27)	(-0.07)	(-0.63)	(-0.46)
$B/M_{i,t\text{-}1}$	0.0062***	0.0062***	0.0060***	0.0060***
	(8.21)	(8.28)	(8.11)	(8.18)
$Beta_{i,t\text{-}1}$	−0.0002	−0.0002	−0.0002	−0.0002
	(-0.23)	(-0.23)	(-0.25)	(-0.26)
$IdioVolt_{i,t\text{-}1}$	−0.0000	−0.0002	−0.0010	−0.0011
	(-0.01)	(-0.13)	(-0.79)	(-0.92)
$Mom_{i,t\text{-}1}$	0.0021**	0.0022**	0.0020**	0.0021**
	(2.05)	(2.10)	(2.01)	(2.05)

where the dependent variable is the raw return for stock *i* in month *t*. The independent variables are measured in month *t*-1. We estimate equation (7) using a Fama and Macbeth (1973) approach, and report average coefficients and *t*-statistics obtained from Newey and West (1987) standard errors in Table 10. We standardize all independent variables in each period by the cross-sectional standard deviation.

In Table 10, we find that the coefficient on *MaxCSpread* is positive and significant in each model specification. Our results suggest that a one standard deviation increase in max CRSP spreads is associated with a 28 to 46 bps increase in next-month returns, controlling for mean CRSP spreads and other liquidity determinants. Therefore, we interpret our results as evidence that max CRSP spreads could be a more accurate proxy for expected illiquidity than mean CRSP spreads. These results are consistent with our findings on max spreads using the MTAQ sample reported in Table 5.

To further examine whether the return premium associated with max spread has changed over time, in Fig. 3 we plot the monthly standardized cross-sectional coefficients from the Fama and Macbeth (1973) regression of *MaxCSpread* on future returns. We find that the majority of the return premia are positive over the extended CRSP sample period. However, the illiquidity premia decline slightly over the sample period.

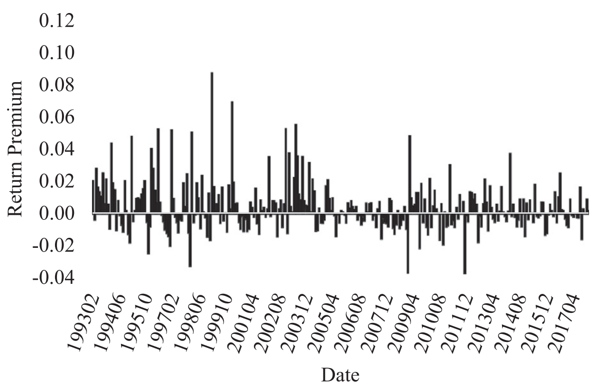

Fig. 3. Maximum CRSP spread return premium.
The figure shows the Fama and Macbeth (1973) regression coefficients on max bid-ask closing spreads for each month in our CRSP sample time period. The variable max CRSP spread is standardized each month by its cross-sectional standard deviation and then regressed on future raw returns.

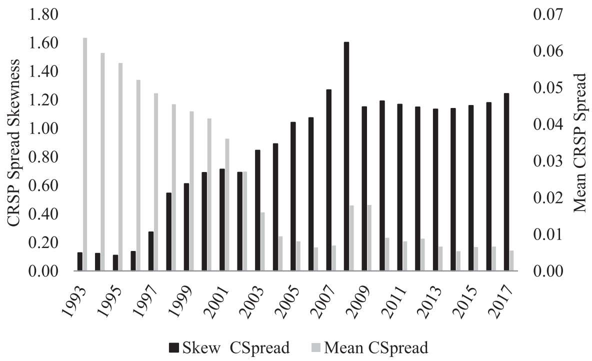

Fig. 4. Skewness and mean CRSP spreads.
The figure shows average closing spread skewness and average percentage closing spreads during the sample time period of 1993–2017.

3.6. Robustness tests: skewness

In this subsection, we examine the skewness of bid-ask spreads, both MTAQ effective spreads and CRSP closing spreads. Roll and Subrahmanyam (2010) examine spread skewness and argue that over time, mean spreads declined while spread skewness increased. Perhaps the return premium associated with bid-ask spreads, as documented in Amihud and Mendelson (1986), is less likely to be found in the diminishing size of average spreads and might instead be subsumed with the increasing level of spread skewness. To illustrate this point, we plot both mean CRSP spreads and closing spread skewness for our sample

Table 11
Fama-MacBeth regressions: Skewness of CRSP and MTAQ spreads.
The table reports the results from estimating the following equation using pooled stock-month observations.

$$Return_{i,t} = \beta_0 + \beta_1 SkewESpread_{i,t-1} + \beta_2 ESpread_{i,t-1} + \beta_3 SkewCSpread_{i,t-1} + \beta_4 CSpread_{i,t-1} + \beta_5 Amihud_{i,t-1} + \beta_6 Turn_{i,t-1} + \beta_7 \ln(Size_{i,t-1}) + \beta_8 \ln(B/M_{i,t-1}) + \beta_9 Beta_{i,t-1} + \beta_{10} IdioVolt_{i,t-1} + \beta_{11} MOM_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the raw return for stock i in month t. The independent variables, which are measured in month t-1 and standardized each month by the cross-sectional standard deviation, include the following: *SkewESpread* is the skewness of intraday percentage effective spreads during a particular month. *ESpread* is the average percentage effective spread. *SkewCSpread* is the skewness of percentage closing spreads during a particular month. *CSpread* is the average percentage closing spread. *Amihud* is average of Amihud's (2002) price impact, which is the ratio of the absolute value of daily returns scaled by daily dollar volume. *Turn* is the share turnover of the average daily volume scaled by shares outstanding (in percent). Ln*(Size)* is the natural log of market capitalization on the last day of each month. Ln*(B/M)* is the natural log of the book-to-market ratio. *Beta* is the beta estimate obtained from the daily CAPM over a six-month rolling period. *IdioVolt* is the standard deviation of daily residual returns over a rolling six-month period, where the residual returns are obtained from a daily Fama and French (1996) and Carhart (1997) four-factor model. *Mom* is the cumulative return for stock i during month t-12 to t-2. We estimate the above equation using a Fama and Macbeth (1973) approach and report average coefficients and t-statistics obtained from Newey and West (1987) standard errors that account for three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	0.0443***	0.0428**	0.0496***	0.0417***
	(3.04)	(2.41)	(5.83)	(4.52)
$SkewESpread_{i,t\text{-}1}$	0.0011***	0.0010***		
	(3.47)	(3.20)		
$ESpread_{i,t\text{-}1}$		−0.0003		
		(-0.20)		
$SkewCSpread_{i,t\text{-}1}$			0.0005*	0.0007***
			(1.89)	(2.64)
$CSpread_{i,t\text{-}1}$				0.0025***
				(3.41)
$Amihud_{i,t\text{-}1}$	0.0008	0.0017**	0.0046***	0.0041***
	(0.78)	(2.18)	(5.67)	(5.33)
$Turn_{i,t\text{-}1}$	−0.0012	−0.0011	−0.0017***	−0.0012**
	(-1.31)	(-1.37)	(-3.15)	(-2.28)
$Size_{i,t\text{-}1}$	−0.0018	−0.0017	−0.0015*	−0.0009
	(-1.52)	(-1.13)	(-1.80)	(-0.94)
$B/M_{i,t\text{-}1}$	0.0046***	0.0045***	0.0060***	0.0059***
	(6.50)	(6.43)	(8.28)	(8.18)
$Beta_{i,t\text{-}1}$	0.0006	0.0003	−0.0002	−0.0002
	(0.43)	(0.25)	(-0.31)	(-0.27)
$IdioVolt_{i,t\text{-}1}$	−0.0013	−0.0011	0.0001	−0.0009
	(-1.28)	(-0.94)	(0.09)	(-0.77)
$Mom_{i,t\text{-}1}$	0.0005	0.0004	0.0019*	0.0020*
	(0.27)	(0.25)	(1.90)	(1.94)

time period in Fig. 4. As seen in the figure, while mean spreads decrease substantially over time, spread skewness dramatically increases.

We next examine whether the return premium associated with max spreads is observed more generally by focusing on the skewness of bid-ask spreads. The motivation for doing so is an attempt to account for the possibility of multicollinearity between max spreads and mean spreads, which existed in our previous tests. Table 11 reports the results from estimating equation (7) using Fama and Macbeth (1973) regressions, but replacing max CRSP spreads with either MTAQ effective spread skewness or CRSP closing spread skewness. To estimate the skewness in effective spreads (*SkewESpread*), we first compute the average effective spreads over 30-min intervals by stock/day. We then take the skewness of those average effective spreads over a particular stock/month. To estimate skewness in closing spreads (*SkewCSpread*), we simply take the skewness of daily closing spreads over a particular stock/month.

In columns (1) and (2) of Table 11, we find positive and significant coefficients on *SkewESpread*. Similarly, in columns (3) and (4) we find that the beta coefficients on *SkewCSpread* are 0.0005 and 0.0007, respectively. These coefficients are statistically significant. Therefore, greater skewness in bid-ask spreads is associated with a positive and significant return premium, holding other factors constant.

3.7. Unreported robustness tests

In unreported robustness tests, we attempt to control for Bali et al.'s (2011) measure of max returns, or the largest daily return for a particular stock during a particular month. We use Fama and Macbeth (1973) regressions to estimate equation (7) including the max return in a particular stock in a particular month as an independent variable. The coefficient on *MaxReturn* is negative and significant, which supports the findings in Bali et al. (2011). After controlling for this variable, we continue to find a positive and economically significant coefficient on max spreads. These results suggest that the return premium associated with max spreads is not explained by the return premium found in max returns.

We also replicate our Fama and Macbeth (1973) regression tests, but include returns in the previous month that account for monthly return reversals instead of max returns. These tests again show that max spreads produce positive and statistically significant coefficients. When we include both return reversals as well as max returns in an additional specification, we still find our measures of spreads produce reliably positive coefficients. Taken together, our unreported results suggest that the max bid-ask spread return premium is robust to additional controls for max returns and/or monthly return reversals.

4. Conclusion

Given the evolution of markets and the multi-faceted nature of liquidity, we propose a new proxy for liquidity uncertainty. In particular, we posit that the maximum bid-ask spread in a particular stock will capture temporary, short-lived spikes in illiquidity and investors, therefore, will discount stocks with higher max spreads vis-à-vis stocks with lower max spreads. If illiquidity is inherently risky, then better proxies should more accurately capture the illiquidity return premium. We hypothesize that stocks with higher maximum bid-ask spreads will command a healthy and significant return premium, even after controlling for liquidity levels.

We find that stocks with the largest maximum spreads have the largest expected returns. For instance, after sorting stocks into portfolios based on max spreads, we find that next-month returns increase monotonically across portfolios. After estimating common multifactor models, we show that stocks in the largest max spread portfolio generate next-month alphas that are approximately 100 bps per month. These results are robust to additional controls for levels of liquidity, including mean spreads.

We also find that max spreads are directly associated with next-month returns. The results from these Fama and Macbeth (1973) regressions are statistically significant and economically meaningful. Specifically, a one standard deviation increase in max spreads (max price impact) is associated with at least a(n) 17 (11) bps increase in next-month returns. These results hold when we control for firm size, volatility, and other measures of illiquidity, such as average spreads and Amihud's (2002) illiquidity. We also find that our results can be replicated using CRSP max closing spreads as an approximation for MTAQ max spreads.

Our results have important policy implications, as Persaud (2003) contends that the general belief among practitioners and regulators is that the primary concern regarding liquidity in financial markets is not the average liquidity level, but the uncertainty of liquidity. We provide evidence that the uncertainty of liquidity is an important piece in identifying the return premium associated with illiquidity. If indeed max spreads are a better proxy for the uncertainty of liquidity, then our findings suggest that only controlling for the bid-ask spread, price impact measure, or the Pástor and Stambaugh (2003) liquidity factor could lead to erroneous inferences.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.finmar.2018.09.003.

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