Financial Management

The Volatility of Bid-Ask Spreads

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This study tests whether the volatility of bid-ask spreads is positively related to expected returns. After controlling for market-risk factors, we find that the average risk-adjusted excess return for stocks in the highest spread volatility quintile is around 50 basis points per month. In a variety of multivariate tests, we find robust evidence of a return premium associated with spread volatility that is both statistically significant and economically meaningful. Our results are robust to controls for a variety of stock characteristics, different tick-size regimes, and other measures of liquidity volatility.

A large stream of research has focused on the relation between liquidity and asset prices. For example, Amihud and Mendelson (1986) model expected returns as a function of bid-ask spreads and show both theoretically and empirically that stocks with larger spreads outperform stocks with smaller spreads. This finding, which is often characterized as the illiquidity premium, has also been documented in Brennan and Subrahmanyam (1996), Datar, Naik, and Radcliffe (1998), Liu (2006), and Han and Lesmond (2011). Given the presence of a significant illiquidity premium, Chordia, Subrahmanyam, and Anshuman (2001) argue that the second moment of liquidity should also be positively related to expected returns under the assumption that agents are averse to the risks associated with the variability in liquidity. Surprisingly, they do not find a direct relation between liquidity volatility and future returns. Instead, they document a significant *negative* association between expected returns and the variability of trading volume and share turnover, which they use as proxies for liquidity. Chordia, Subrahmanyam, and Anshuman (2001) offer a plausible explanation for this peculiar result by suggesting that trading volume and turnover may not properly measure liquidity. Similar arguments that variation in trading volume and turnover might not be good proxies for liquidity uncertainty are also made in Hasbrouck (2006) and Johnson (2008). We reexamine this relationship but use the volatility of the bid-ask spread as our measure of liquidity volatility, which was not available with a sufficient time series at the time of Chordia, Subrahmanyam, and Anshuman (2001).

The assertion that variability in liquidity will lead to higher expected returns stems from the idea that observable fluctuations in liquidity might affect investors' expectations about future trading costs. With higher expected trading costs, stocks with greater variation in liquidity might command a premium in addition to the well-documented illiquidity premium. Although Chordia, Subrahmanyam, and Anshuman (2001) do not provide a theoretical model to develop the predicted relation between the volatility of liquidity and expected returns, more recent studies have provided an indirect theoretical framework. For instance, Acharya and Pedersen (2005) adjust the traditional capital asset pricing model (CAPM) to account for liquidity costs and show that a stock's expected return depends on its expected liquidity and a series of covariances between the liquidity of the

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stock and (i) the stock's return, (ii) the return of the market, and (iii) the liquidity of the market. Admittedly, their analysis is grounded in these liquidity covariances and the expected (or average cost) of liquidity and is agnostic to the variance of liquidity. However, Persuad (2003) suggests that there is also 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.

This study is not the first attempt to reconcile the peculiar findings in Chordia, Subrahmanyam, and Anshuman (2001). For example, Pereira and Zhang (2010) analyze the expected utility of investors to help explain the negative relation between the variability in trading activity and expected returns. They argue that higher liquidity volatility provides a better opportunity for investors to time their trades, which would lead to price premiums and subsequent underperformance for stocks with high liquidity volatility. In their empirical tests, Pereira and Zhang (2010) use Amihud's (2002) measure of illiquidity along with trading volume and share turnover when estimating liquidity volatility. Results in their study provide additional evidence of a negative relation between expected returns and the volatility of liquidity. However, Amihud's (2002) measure, which is the ratio of the absolute value of daily returns to daily trade volume, might also present some challenges in properly identifying a liquidity volatility return premium. For instance, the negative relation between expected returns and the volatility of Amihud's (2002) illiquidity measure might simply be capturing part of the commonly found negative relation between expected returns and the idiosyncratic volatility of daily returns (Ang et al., 2006).

We extend this line of research by testing for a significant return premium associated with the variability of bid-ask spreads (spread volatility hereafter).[1] Consistent with the idea in Chordia, Subrahmanyam, and Anshuman (2001), we find strong evidence that stocks with higher levels of spread volatility outperform stocks with lower levels of spread volatility. The return premium associated with spread volatility is not only statistically significant, but it is also economically meaningful. For instance, during our sample time period, stocks in the highest spread volatility quintile have next-month excess returns ranging from 38 basis points to 60 basis points. This return premium is also robust to a variety of factors that have been shown to explain expected returns, such as the market risk premium, small minus big (SMB), high minus low (HML), the momentum factor, and the Pastor and Stambaugh (2003) illiquidity factor. The spread volatility premium is also robust to controls for different tick-size regimes (e.g., pre- and postdecimalization).

We also examine the relation between the spread volatility premium and the proxies for the variability of liquidity used in Chordia, Subrahmanyam, and Anshuman (2001) and Pereira and Zhang (2010). Interestingly, we are able to provide some evidence that confirms the findings in both of these studies as the volatility of trading volume and the volatility of share turnover are negatively related to future returns. However, we only find this negative relation in stocks with the highest spread volatility. Similarly, we are only able to observe a negative relation between the volatility of Amihud's (2002) illiquidity and next-month returns in stocks with the lowest spread volatility. After including controls for these measures of liquidity volatility, our multivariate results still show a positive and significant relation between spread volatility and

[1] While prior research has used the term liquidity risk to describe measures of both liquidity and the volatility of liquidity (see Pastor and Stambaugh, 2003; Johnson, 2008; Sadka, 2010), our definition of liquidity risk is most similar to Acharya and Pedersen (2005), which defines liquidity risk as uncertainty over future illiquidity costs. Stocks with higher variability in liquidity have less certain levels of expected future liquidity. Further, although prior research that tests the hypothesis in Chordia, Subrahmanyam, and Anshuman (2001) focuses on the variability in volume, share turnover, and price impact. We return to Amihud and Mendelson's (1986) original proxy for liquidity, the bid-ask spread, and test for a return premium associated with spread volatility.

expected returns. In additional tests, we find that the spread volatility premium is largest in stocks with the smallest market capitalization and the highest book-to-market ratios. We also find that the spread volatility premium is robust to controls for idiosyncratic volatility. Combined with our initial results, these findings support the original assertion in Chordia, Subrahmanyam, and Anshuman (2001) and indicate that spread volatility is indeed an important determinant of expected returns.

The remainder of this paper is organized as follows. Section I describes the data used in the analysis. In Section II, we present our empirical tests and results with some concluding remarks in Section III.

I. Data Description

In this section, we describe the data used throughout the analysis. To measure bid-ask spreads, we follow Roll and Subrahmanyam (2010) and Chung and Zhang (2014) and obtain daily closing bid and ask prices for the universe of stocks available at the Center for Research on Security Prices (CRSP).[2] For each stock-month observation, we estimate the mean and the standard deviation of closing spreads, where spreads are calculated as the difference between the ask price and the bid price scaled by the midpoint of the closing ask and bid prices. From CRSP, we also gather daily and monthly returns, volume, market capitalization, and prices. Using CRSP daily returns, we estimate idiosyncratic volatility or the standard deviation of daily residual returns, where residual returns are errors from a daily four-factor model. We also estimate monthly capital asset pricing model (CAPM) betas (*Beta*) using daily stock returns, market returns, and risk-free rates, which are approximated by one-month T-Bill rates. We note that the measures of idiosyncratic volatility and betas are estimated each month using a rolling six-month window. From Compustat, we obtain quarterly book-to-market ratios, but require these ratios to be positive. Similarly, we require that closing bid-ask spreads to be positive. We also include a number of other commonly used data restrictions. For instance, we eliminate stocks with prices less than \$5, stocks with prices greater than \$1,000, and stocks with bid-ask spreads greater than 50%. The final sample used throughout the analysis consists of 13,757 unique stocks and 915,837 stock-month observations from 1993 to 2012.[3]

Table I reports statistics that describe the sample. *Price* is the closing monthly price according to CRSP while *Size* is the market capitalization or the product of the CRSP price and shares outstanding. *Turn* is the share turnover, which is the ratio of the monthly trading volume scaled by shares outstanding (in percent), while *IdioVolt* is our measure of idiosyncratic volatility. *Beta* is our estimate of the CAPM beta and *B/M* is the book-to-market ratio obtained from Compustat. *SPRD* is the mean of daily spreads during a particular month and $\sigma(SPRD)$ is the standard deviation of daily spreads. Further, $\sigma(vol)$, $\sigma(turn)$, and $\sigma(illiq)$ are the volatility of daily trading volume, the volatility of daily turnover, and the volatility of Amihud's (2002) measure of illiquidity, which is the ratio of the absolute value of daily returns scaled by volume (in 1,000,000s).

We note several important regulatory changes that are present during our sample time period. On June 24, 1997, the New York Stock Exchange (NYSE) reduced the minimum price variation

[2] Chung and Zhang (2014) show that the use of CRSP closing bid-ask spreads is a very close approximation to using high frequency data when calculating bid-ask spreads. Roll and Subrahmanyam (2010) also find that closing bid-ask spreads in CRSP properly approximate intraday bid-ask spreads.

[3] We replicate much of our analysis while not including these restrictions and find qualitatively similar results to those reported in this article.

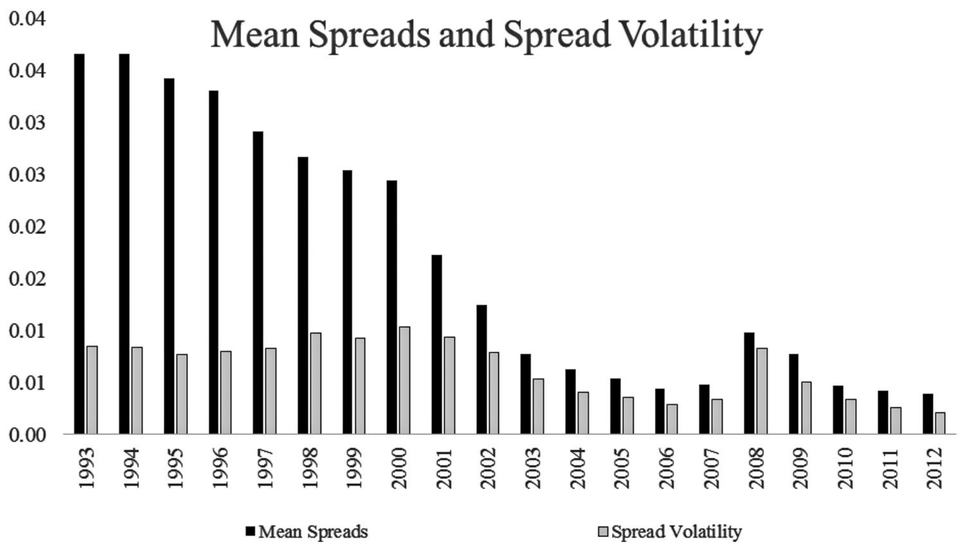
Table I. Summary Statistics

The table reports a summary of statistics of the variables used throughout the analysis during the entire time period. *Price* is the CRSP closing price at the end of each month while *Size* if the market capitalization using shares outstanding and closing prices at the end of each month. *B/M* is the book-to-market ratio gathered from CRSP and Compustat. Turn is the share turnover or the ratio of the monthly volume to shares outstanding (in percent). *Idiovolt* is a measure of idiosyncratic volatility and is obtained by taking the standard deviation of the daily residual returns from a traditional four-factor model during a rolling 6-month window. Likewise, *Beta* is obtained from estimating a Capital Asset Pricing Model using daily returns, risk-free rates (one-month T-Bill rates), and market returns during the same rolling 6-month window. *SPRD* is the average daily closing spread taken at the monthly level. $\sigma(SPRD)$ is the spread volatility or the standard deviation of the daily closing spreads taken at the monthly level. $\sigma(vol)_{i,t}$ is the natural log of the standard deviation of volume; $\sigma(turn)_{i,t}$ is the natural log of the standard deviation of share turnover; $\sigma(illiq)_{i,t}$ is the natural log of the standard deviation of Amihud's (2002) illiquidity, which is the absolute value of the daily returns scaled by daily volume (in 100,000s). Panel A reports the summary statistics during the entire time period (1993 to 2013). Panel B reports the summary statistics during the predecimalization period (1993 to 2000). Panel C presents the summary statistics during the postdecimalization period (2001 to 2013).

	Mean (1)	**Std. Dev (2)**	**Minimum (3)**	**25th Perc. (4)**	**Median (5)**	**75th Perc. (6)**	**Maximum (7)**
Panel A. Entire Time Period							
Price	24.43	24.76	5.00	10.65	18.38	30.68	1000.00
Size	2.7185	13.0952	0.0089	0.0957	0.3250	1.2104	579.2423
B/M	0.6351	2.7612	0.0047	0.0340	0.0582	0.0926	5.9939
Turn	6.9400	23.0555	0.0767	1.5532	3.7742	8.2382	45.1740
IdioVolt	0.0266	0.0164	0.0070	0.0157	0.0229	0.0335	0.0792
Beta	0.8820	2.8044	−1.0034	0.4138	0.8572	1.2842	3.2111
$SPRD_{i,t}$	0.0190	0.0251	0.0003	0.0025	0.0109	0.0257	0.4952
$\sigma(SPRD)_{i,t}$	0.0069	0.0097	0.0001	0.0016	0.0044	0.0090	0.5641
$\sigma(vol)_{i,t}$ (in 1000s)	2,393.75	1,391.21	.44	13.67	56.10	198.46	286,300.89
$\sigma(turn)_{i,t}$	5.4105	26.1528	0.1154	1.1928	2.5741	5.5317	13,355.19
$\sigma(illiq)_{i,t}$	0.2138	0.3818	0.0000	0.0001	0.0190	0.2768	2.3993
Panel B. 1993 to 2000 (Predecimalization)							
$SPRD_{i,t}$	0.0366	0.0280	0.0029	0.0131	0.0228	0.0391	0.4952
$\sigma(SPRD)_{i,t}$	0.0087	0.0078	0.0002	0.0039	0.0069	0.0112	0.3492
$\sigma(vol)_{i,t}$ (in 1000s)	137.90	510.05	0.44	10.14	35.32	109.28	63,573.24
$\sigma(turn)_{i,t}$	5.2706	23.2532	0.1154	1.1006	2.4046	5.4341	10473.88
$\sigma(illiq)_{i,t}$	0.1574	0.5296	0.0000	0.0007	0.0661	0.7290	2.3854
Panel C. 2001 to 2012 (Postdecimalization)							
$SPRD_{i,t}$	0.0077	0.0149	0.0003	0.0012	0.0027	0.0082	0.4937
$\sigma(SPRD)_{i,t}$	0.0051	0.0109	0.0001	0.0008	0.0020	0.0056	0.5641
$\sigma(vol)_{i,t}$ (in 1000s)	444.76	1,871.43	0.55	20.89	95.86	332.18	286,300.89
$\sigma(turn)_{i,t}$	5.5451	28.6677	0.1211	1.2967	2.7290	5.6174	13,355.19
$\sigma(illiq)_{i,t}$	0.2715	0.5321	0.0000	0.0001	0.0054	0.2768	2.3993

Figure 1.

The Table Reports the Average Daily Closing Spread (Mean Spread) During Each Year of the Sample Time Period as well as the Standard Deviation of the Daily Closing Spread (Spread Volatility) During Each Year.



for trading stocks from 1/8th of dollars to 1/16th of dollars. Again, on January 29, 2001, the NYSE reduced the minimum tick size from 1/16th of dollars to pennies. Shortly after, the Nasdaq stock market also introduced decimalization or the trading and quoting of stocks on decimals instead of fractions of dollars. Because these tick-size reductions affected liquidity (see Goldstein and Kavajecz (2000) and Bessembinder (2003), our tests for a return premium associated with spread volatility might need to control for these different tick-size environments. Therefore, Panel A of Table I reports the results for the entire sample time period while Panels B and C present mean spreads and the four measures of liquidity volatility during the predecimalization and postdecimalization periods, respectively.

Panel A of Table I shows that the average stock has a price of $24.43, a market cap of $2.7185 billion, and a book-to-market ratio of 0.6351. We also find that, for the average stock, monthly turnover is 6.94, idiosyncratic volatility is 2.66% and beta is 0.8820. The mean spread for the average stock during the entire time period is 0.0190 or 1.9% while the spread volatility of the average stock is 0.0069 or 0.69%.

In Table I, we also find that the mean spread for the average stock was highest during the predecimalization period as the average stock had a mean spread of 0.0366. Panel C shows that mean spreads decreased across time as the mean spread was 0.0077 during the postdecimalization period. While mean spreads have appeared to decrease across time, the standard deviation of spreads has also decreased but at a much lower rate. In particular, we find that the spread volatility for the average stock decreased from 0.0087 to 0.0051 in Panels B and C. If anything, the other measures of liquidity volatility increased rather than decreased across the latter two panels.

Figure 1 provides a graphical representation of the both mean spreads and spread volatility across each year of our sample time period. The figure shows that mean spreads are generally decreasing across time although not monotonically. For instance, mean spreads in 1994 were slightly higher than in 1993 and spreads during the recent financial crisis were twice as large as spreads during the years preceding the crisis. Spread volatility, on the other hand, remained relatively constant from 1993 to 2002 and then subsequently decreased until the 2008 financial crisis. The mean spreads for our sample are similar to the mean spreads reported in Chung and Zhang (2014).

II. Empirical Results

A. Correlation: Liquidity Volatility and Other Stock Characteristics

We begin by estimating Pearson correlation coefficients for the various characteristics used throughout the analysis. We report this correlation matrix in Table II. The variables included are the mean spread ($SPRD_{i,t}$), the standard deviation of the daily spreads ($\sigma(SPRD_{i,t})$), the standard deviation of daily trading volume ($\sigma(vol_{i,t})$), the standard deviation of share turnover ($\sigma(turn_{i,t})$), and the standard deviation of Amihud's (2002) illiquidity ($\sigma(illiq_{i,t})$). We also include in the correlation matrix, the following variables: the closing price according to CRSP (*Price*), the market capitalization (*Size*), the book-to-market ratio (*B*/*M*), the share turnover (*Turn*), our measure of idiosyncratic volatility (*IdioVolt*), and our measure of beta (*Beta*).

In the first row, we find that mean spreads are directly related to spread volatility, illiquidity volatility, book-to-market ratios, and idiosyncratic volatility. Further, means spreads are negatively related to volume volatility, turnover volatility, prices, size, turnover, and beta. We note that *p* values are reported in brackets. These correlations are important for a few reasons. First, we find that strong positive correlation between mean spreads and spread volatility. Multivariate tests examining the return premium associated with spread volatility must account for the possibility of multicollinearity between mean spreads and spread volatility. Second, other measures of liquidity volatility have varying levels of correlation with mean spreads. For instance, while mean spreads are directly related to illiquidity volatility, a negative correlation exists between mean spreads and both volume volatility and turnover volatility. These results question whether previous measures of liquidity volatility are indeed capturing illiquidity or some other variable. While outside the scope of our analysis, this question might provide a fruitful avenue for future research.

In the second row, we find that spread volatility is negatively associated with volume volatility, turnover volatility, prices, size, turnover, and beta. Further, spread volatility is positively correlated with illiquidity volatility, book-to-market ratios, and idiosyncratic volatility. These findings also question whether the liquidity volatility measures used in prior studies are indeed capturing the same type of information that spread volatility is capturing. It is possible that volume volatility and turnover volatility are measures of heterogeneous beliefs among investors (Berkman et al., 2009), which could explain the negative relationship between these variables and future returns as found in Roll, Subrahmanyam, and Anshuman (2001). Again, we will leave these tests to future research. The cross-correlations are provided in the remaining rows and columns in Table II.

B. The Spread Volatility Return Premium: A Fama-MacBeth Approach

In this section, and those that follow, we examine the cross-sectional relation between next month's excess returns and spread volatility in a multivariate setting. Following much of the empirical asset pricing literature, we use a Fama and MacBeth (1973) approach to examine the spread volatility return premium. We begin by estimating our base model using pooled

Table II. Correlation

The table reports the Pearson correlation coefficients with corresponding *p* values (in brackets) for the variables used throughout the analysis. *SPRD* is the average daily closing spread taken at the monthly level. $\sigma(SPRD)$ is the spread volatility or the standard deviation of the daily closing spreads taken at the monthly level. $\sigma(vol)_{i,t}$ is the natural log of the standard deviation of volume; $\sigma(turn)_{i,t}$ is the natural log of the standard deviation of share turnover; $\sigma(illiq)_{i,t}$ is the natural log of the standard deviation of Amihud's (2002) illiquidity, which is the absolute value of the daily returns scaled by daily volume (in 100,000s). *Price* is the CRSP closing price at the end of each month while *Size* if the market capitalization using shares outstanding and closing prices at the end of each month. *B*/*M* is the book-to-market ratio gathered from CRSP and Compustat. Turn is the share turnover or the ratio of the monthly volume to shares outstanding (in percent). *Idiovolt* is a measure of idiosyncratic volatility and is obtained by taking the standard deviation of the daily residual returns from a traditional four-factor model during a rolling 6-month window. Likewise, *Beta* is obtained from estimating a Capital Asset Pricing Model using daily returns, risk-free rates, and market returns during the same rolling 6-month window.

	SPRD **(1)**	**σ(*SPRD*) (2)**	**σ(*vol*) (3)**	**σ(*turn*) (4)**	**σ(*illiq*) (5)**	***Price*** **(6)**	***Size*** **(7)**	***B/M*** **(8)**	***Turn*** **(9)**	***IdioVolt*** **(10)**	***Beta*** **(11)**
SPRD	1.0000	0.5997	-0.1195	−0.0370	0.1431	−0.2340	−0.1207	0.0207	−0.1046	0.3218	−0.0264
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
σ(*SPRD*)		1.0000	−0.0955	−0.0189	0.1905	−0.2034	−0.1024	0.0151	−0.0713	0.3206	−0.0213
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
σ(*vol*)			1.0000	0.0852	−0.0116	0.0545	0.3772	−0.0040	0.1231	−0.0147	0.0095
				(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
σ(*turn*)				1.0000	−0.0076	0.0026	−0.0168	0.1150	0.8805	0.1121	0.0065
					(<0.0001)	(0.015)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
σ(*illiq*)					1.0000	−0.0306	−0.0114	0.0012	−0.0144	0.0578	−0.0076
						(<0.0001)	(<0.0001)	(0.262)	(<0.0001)	(<0.0001)	(<0.0001)
Price						1.0000	0.2400	0.0046	0.0430	−0.2468	0.0079
							(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Size							1.0000	−0.0043	0.0019	−0.1246	0.0050
								(<0.0001)	(0.077)	(<0.0001)	(<0.0001)
B/*M*								1.0000	0.0923	−0.0037	−0.0017
									(<0.0001)	(0.0004)	(0.106)
Turn									1.0000	0.1173	0.0132
										(<0.0001)	(<0.0001)
IdioVolt										1.0000	0.0255
											(<0.0001)
Beta											1.0000

stock-month observations.

$$
\begin{aligned}
Ex - Ret_{i,t+1} = {} & \beta_0 + \beta_1 \sigma(SPRD)_{i,t} + \beta_2 SPRD_{i,t} + \beta_3 Beta_{i,t} + \beta_4 \ln(Size_{i,t}) \\
& + \beta_5 \ln(B/M_{i,t}) + \beta_6 Ret_{i,t-6,t-1} + \beta_7 \ln(Turn_{i,t}) + \beta_8 \ln(Price_{i,t}) \\
& + \beta_9 Idiovolt_{i,t} + \varepsilon_{i,t+1}. \qquad (1)
\end{aligned}
$$

The dependent variable is excess return or the difference between the raw return for stock i during month $t + 1$ and the one-month T-Bill rate in month $t + 1$. The independent variables include the following: $\sigma(SPRD_{i,t})$ is the standard deviation of the daily closing spreads for each stock i during month t; $\ln(SPRD_{i,t})$ is the natural log of average spreads for each stock i during month t.[4] *Beta* is obtained from estimating a Capital Asset Pricing Model; $\ln(Size_{i,t})$ is the natural log of market capitalization using shares outstanding and closing prices at the end of each month; $\ln(B/M)$ is the natural log of the book-to-market ratio; $Ret_{i,t-6,t-1}$ is the cumulative return for stock i from month $t - 6$ to $t - 1$; $\ln(Turn_{i,t})$ is the natural log of share turnover; $\ln(Price)$ is the natural log of the CRSP closing price at the end of each month; *Idiovolt* is our measure of idiosyncratic volatility. We report t-statistics that are obtained using Newey-West (1987) standard errors with three lags.

Table III reports the results from the Fama-MacBeth regressions. In Column (1), we find that spread volatility produces a positive and significant estimate (estimate = 0.1933, t-statistic = 2.93), which is consistent with the idea of a return premium associated with the variability of bid-ask spreads. In economic terms, a 1% increase in spread volatility results in a nearly 20 basis point increase in next month's returns. In annual terms, this estimate suggests that the return premium associated with spread volatility is approximately 2.5%. Column (2) shows the results when we include a control for mean spreads along with some other traditional controls. Again, we find that the coefficient on spread volatility is positive and significant (estimate = 0.1573, t-statistic = 2.65). We also find that book-to-market ratios and past returns are strong predictors of next-month excess returns (Fama and French, 1992; Jegadeesh and Titman, 1993). Further, and perhaps more importantly, we do not find that mean spreads are important predictors of next-month returns. Column (3) includes the full specification but excludes our variable of interest—spread volatility. Without the inclusion of spread volatility, we find that the estimate for mean spreads is both positive and reliably different from zero (estimate = 0.1928, t-statistic = 2.47). However, in column (4), the full specification, we find that while spread volatility produces a positive and significant estimate (estimate = 0.2195, t-statistic = 4.27), the coefficient on the natural log of mean spreads is no longer significant (estimate = 0.0813, t-statistic = 0.93). Consistent with findings from Ang et al. (2006), we also find that idiosyncratic volatility produces a reliably negative estimate (estimate = −0.1464, t-statistic = −1.71). The main conclusion from this table is that, after controlling for other factors that have been shown to influence next-month excess returns, we show that spread volatility commands a healthy return premium.

[4] We use the natural log of mean spreads instead of mean spreads for two reasons. First, the log of mean spreads has more of a normal distribution and second, using the natural log of mean spreads seems to reduce the potential for multicollinearity bias. Recall from Table II, the correlation between mean spreads and spread volatility is remarkably high. Variance inflation factors for mean spread and spread volatility in a standard ordinary least square (OLS) estimation of Equation (1) show that while spread volatility produces a factor less than 1.5, mean spreads produces a factor slightly greater than 2. When using the natural log of the mean spreads, the variance inflation factor for spread volatility is effectively 1 while the factor for the log of mean spreads is about 1.5.

Table III. Fama-MacBeth Regressions

The table reports the results from estimating the following equation using Fama-MacBeth (1973) regressions.

$$Ex - Ret_{i,t+1} = \beta_0 + \beta_1\sigma(SPRD)_{i,t} + \beta_2 \ln(SPRD_{i,t}) + \beta_3 Beta_{i,t} + \beta_4 \ln(Size_{i,t}) + \beta_5 \ln(B/M_{i,t}) + \beta_6 Ret_{i,t-6,t-1} + \beta_7 \ln(Turn_{i,t}) + \beta_8 \ln(Price_{i,t}) + \beta_9 Idiovolt_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is excess return or the difference between the raw return for stock i during month $t+1$ and the one-month T-Bill rate in month $t+1$. The independent variables include the following: $\sigma(SPRD_{i,t})$ is the standard deviation of the daily closing spreads for each stock i during month t; $\ln(SPRD_{i,t})$ is the natural log of average spreads for each stock i during month t. *Beta* is obtained from estimating a Capital Asset Pricing Model using daily returns, risk-free rates, and market returns using a rolling 6-month window; $\ln(Size_{i,t})$ is the market capitalization using shares outstanding and closing prices at the end of each month; $\ln(B/M_{i,t})$ is the natural log of the book-to-market ratio; $Ret_{i,t-6,t-1}$ is the cumulative return for stock i from month $t-6$ to $t-1$; $\ln(Turn_{i,t})$ is the natural log of share turnover; ln(*Price*) is the natural log of the CRSP closing price at the end of each month; *Idiovolt* is a measure of idiosyncratic volatility and is obtained by taking the standard deviation of the daily residual returns from a traditional four-factor model using a rolling 6-month window. We report t-statistics below each estimate that are obtained using Newey-West (1987) standard errors with three lags.

	All Observations			
	(1)	(2)	(3)	(4)
Intercept	0.7926**	1.3041**	2.5474***	1.9814***
	(2.06)	(2.09)	(4.34)	(3.24)
$\sigma(SPRD)_{i,t}$	0.1933***	0.1573***	0.1928**	0.2195***
	(2.93)	(2.65)	(2.47)	(4.27)
$\ln(SRRD_{i,t})$		0.0751	0.0044	0.0813
		(0.66)	(0.06)	(0.93)
$Beta_{i,t}$		0.0799	0.0208	0.0106
		(0.78)	(0.47)	(0.14)
$\ln(Size_{i,t})$		0.0316	0.2821***	0.0184
		(0.62)	(5.19)	(0.41)
$\ln(B/M_{i,t})$		0.3323***	0.0111***	0.2835***
		(4.96)	(3.72)	(5.17)
$Ret_{i,t-6,t-1}$		0.0088***	0.0796	0.0114***
		(2.75)	(1.14)	(3.80)
$\ln(Turn_{i,t})$			−0.1330	0.0878
			(−1.18)	(1.25)
$\ln(Price_{i,t})$			−0.1213	−0.1450
			(−1.45)	(−1.30)
$IdioVolt_{i,t}$				−0.1464*
				(−1.71)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

C. The Spread Volatility Return Premium and Different Tick-Size Environments

Next, we examine whether the return premium associated with spread volatility, as found in our Fama-MacBeth (1973) results, is robust to the different tick-size environments. In particular, we estimate the Equation (1) for the predecimalization period (January 1993 to January 2001)

Table IV. Fama-MacBeth Regressions Pre- and Post-decimalization Periods

The table reports the results from estimating the following equation using Fama-MacBeth (1973) regressions during the predecimalization period (1993 to 2000) and the postdecimalization period (2001 to 2013).

$$Ex - Ret_{i,t+1} = \beta_0 + \beta_1 \sigma(SPRD)_{i,t} + \beta_2 \ln(SPRD_{i,t}) + \beta_3 Beta_{i,t} + \beta_4 \ln(Size_{i,t}) + \beta_5 \ln(B/M_{i,t}) + \beta_6 Ret_{i,t-6,t-1} + \beta_7 \ln(Turn_{i,t}) + \beta_8 \ln(Price_{i,t}) + \beta_9 Idiovolt_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is excess return or the difference between the raw return for stock i during month $t + 1$ and the one-month T-Bill rate in month $t + 1$. The independent variables include the following: $\sigma(SPRD_{i,t})$ is the standard deviation of the daily closing spreads for each stock i during month t; $\ln(SPRD_{i,t})$ is the natural log of average spreads for each stock i during month t. *Beta* is obtained from estimating a Capital Asset Pricing Model using daily returns, risk-free rates, and market returns using a rolling 6-month window; $\ln(Size_{i,t})$ is the market capitalization using shares outstanding and closing prices at the end of each month; $\ln(B/M_{i,t})$ is the natural log of the book-to-market ratio; $Ret_{i,t-6,t-1}$ is the cumulative return for stock i from month $t - 6$ to $t - 1$; $\ln(Turn_{i,t})$ is the natural log of share turnover; ln(*Price*) is the natural log of the CRSP closing price at the end of each month; *Idiovolt* is a measure of idiosyncratic volatility and is obtained by taking the standard deviation of the daily residual returns from a traditional four-factor model using a rolling 6-month window. We report t-statistics below each estimate that are obtained using Newey-West (1987) standard errors with three lags.

	1993 to 2000 (Predecimalization)		**2001 to 2013 (Postdecimalization)**	
	(1)	**(2)**	**(3)**	**(4)**
Intercept	0.7175	1.1578	0.8430	2.5347***
	(1.39)	(1.12)	(1.56)	(3.52)
$\sigma(SPRD)_{i,t}$	0.2526**	0.3068***	0.1534**	0.1608**
	(2.13)	(3.81)	(2.03)	(2.48)
$\ln(SRRD_{i,t})$		0.2515		−0.0330
		(1.57)		(−0.35)
$Beta_{i,t}$		0.0657		−0.0263
		(1.17)		(−0.21)
$\ln(Size_{i,t})$		0.1443**		−0.0662
		(1.97)		(−1.26)
$\ln(B/M_{i,t})$		0.4637***		0.1625***
		(4.53)		(3.19)
$Ret_{i,t-6,t-1}$		0.0190***		0.0062
		(5.11)		(1.52)
$\ln(Turn_{i,t})$		0.1531		0.0439
		(1.26)		(0.53)
$\ln(Price_{i,t})$		−0.0964		−0.1777
		(−0.53)		(−1.30)
$IdioVolt_{i,t}$		−0.0745		−0.1948*
		(−0.52)		(−1.86)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

and the postdecimalization period (February 2001 to December 2012).[5] As before, we report t-statistics that are obtained from Newey-West (1987) standard errors.

[5] While the NYSE reduced the minimum tick size to pennies in January 2001, Nasdaq did not reduce the minimum tick size until April 2001. In unreported tests, we use months before April 2001 as the predecimalization period and find qualitatively similar results to those reported in this article.

Columns (1) and (3) of Table IV show the results from simple regressions while Columns (2) and (4) present the findings from the full specification. Given that the results are qualitatively similar between columns, we choose to only discuss the results from the full specification for brevity. In Column (2), we find that, similar to Table III, book-to-market ratios and past returns are strong predictors of future excess returns. We also find some evidence that the natural log of market capitalization produces a positive and significant estimate. After including these, and other controls, we still find that spread volatility produces a reliably positive estimate (estimate = 0.3068, t-statistic = 3.81). In economic terms, the coefficient on spread volatility is nearly 40% greater than the corresponding coefficient in the full specification in Table III

When examining the postdecimalization period in Column (4), we again find that book-to-market ratios predict next-month excess returns. We also find some evidence that idiosyncratic volatility predicts negative excess returns, which is similar to findings in Ang et al. (2006). Again, we find that the coefficient on spread volatility is positive and reliably different from zero (estimate = 0.1608, t-statistic = 2.48). We note that while the magnitude of the coefficient decreases by almost 50% from Column (2), the coefficient is still economically meaningful. For instance, a one standard deviation increase in spread volatility results in an 18 basis point increase in next-month excess returns, which represents nearly 2.2% in annual terms. The results from the tests in this subsection seem to indicate that although the return premium associated with spread volatility is much stronger during the predecimalization period, a significant return premium still exists during the postdecimalization period.

D. The Spread Volatility Return Premium and Specific Controls for Multicollinearity

Thus far, we have found evidence of a return premium associated with spread volatility that is robust to various tick-size regimes. However, as mentioned in our discussion of Table II, we find strong correlation between spread volatility and mean spreads. In this section, we attempt to address the possibility of multicollinearity bias. To do so, we slightly adjust Equation (1) by estimating the following equation using the traditional Fama-MacBeth (1973) approach.

$$
\begin{aligned}
Ex - Ret_{i,t+1} = {} & \beta_0 + \beta_1 \sigma(SPRD)^{\text{adj}}_{i,t} + \beta_2 \ln(SPRD_{i,t}) + \beta_3 Beta_{i,t} + \beta_4 \ln(Size_{i,t}) \\
& + \beta_5 \ln(B/M_{i,t}) + \beta_6 Ret_{i,t-6,t-1} + \beta_7 \ln(Turn_{i,t}) + \beta_8 \ln(Price_{i,t}) \\
& + \beta_9 Idiovolt_{i,t} + \varepsilon_{i,t+1}. \qquad (2)
\end{aligned}
$$

In Equation (2), the dependent variable and the independent variables are similar to those in Equation (1). The only difference is the variable $\sigma(SPRD_{i,t})^{\text{adj}}$. $\sigma(SPRD_{i,t})^{\text{adj}}$ is the residual from a regression where the dependent variable is $\sigma(SPRD_{i,t})$ and the independent variable is $SPRD_{i,t}$. The regression is estimated for each stock. These residuals capture the portion of spread volatility that is orthogonal to mean spreads.

Table V shows the results from estimating Equation (2). As before, t-statistics, which are obtained from Newey-West (1987) standard errors, are reported in parentheses. Column (1) shows a simple regression where the independent variable of interest is $\sigma(SPRD_{i,t})^{\text{adj}}$. The coefficient produced by this adjusted measure of spread volatility is both positive and statistically significant (estimate = 0.1942, t-statistic = 3.03). Column (2) includes the same controls as in Column (2) of Table III. As before, we find that book-to-market ratios and past returns are strong predictors of future excess returns. Again, we find that $\sigma(SPRD_{i,t})^{\text{adj}}$ produces a positive estimate that reliably different that zero (estimate = 0.1960, t-statistic = 3.57). The third column reports the results

Table V. Fama-MacBeth Regressions

The table reports the results from estimating the following equation using Fama-MacBeth (1973) regressions.

$$Ex - Ret_{i,t+1} = \beta_0 + \beta_1 \sigma(SPRD_{i,t})^{\text{adj}} + \beta_2 \ln(SPRD_{i,t}) + \beta_3 Beta_{i,t} + \beta_4 \ln(Size_{i,t}) + \beta_5 \ln(B/M_{i,t}) + \beta_6 Ret_{i,t-6,t-1} + \beta_7 \ln(Turn_{i,t}) + \beta_8 \ln(Price_{i,t}) + \beta_9 Idiovolt_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is excess return or the difference between the raw return for stock i during month $t+1$ and the one-month T-Bill rate in month $t+1$. The independent variables include the following: $\sigma(SPRD_{i,t})^{\text{adj}}$ is the residual from a regression where we regress $\sigma(SPRD_{i,t})$ on $SPRD_{i,t}$ by stock to account for the possibility of multicollinearity; ln($SPRD_{i,t}$) is the natural log of average spreads for each stock i during month t. *Beta* is obtained from estimating a Capital Asset Pricing Model using daily returns, risk-free rates, and market returns using a rolling 6-month window; ln($Size_{i,t}$) is the market capitalization using shares outstanding and closing prices at the end of each month; ln(*B/M*) is the natural log of the book-to-market ratio gathered; $Ret_{i,t-6,t-1}$ is the cumulative return for stock i from month $t-6$ to $t-1$; ln($Turn_{i,t}$) is the natural log of share turnover; ln(*Price*) is the natural log of the CRSP closing price at the end of each month; *Idiovolt* is a measure of idiosyncratic volatility and is obtained by taking the standard deviation of the daily residual returns from a traditional four-factor model using a rolling 6-month window. We report t-statistics below each estimate that are obtained using Newey-West (1987) standard errors with three lags.

	(1)	(2)	(3)
Intercept	0.9246**	1.8136***	2.5173***
	(2.44)	(3.05)	(4.34)
$\sigma(SPRD_{i,t})^{\text{adj}}$	0.1942***	0.1960***	0.1728***
	(3.03)	(3.57)	(2.89)
ln($SRRD_{i,t}$)		0.1631	0.1880**
		(1.62)	(2.37)
$Beta_{i,t}$		0.0697	0.0003
		(0.67)	(0.04)
ln($Size_{i,t}$)		0.0320	0.0197
		(0.61)	(0.45)
ln($B/M_{i,t}$)		0.3306***	0.2841***
		(4.84)	(5.22)
$Ret_{i,t-6,t-1}$		0.0090***	0.0112***
		(2.81)	(3.76)
ln($Turn_{i,t}$)			0.0762
			(1.08)
ln($Price_{i,t}$)			−0.1266
			(−1.13)
$IdioVolt_{i,t}$			−0.1203
			(−1.44)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

from the full specification. A couple results are noteworthy. First, we find that the natural log of mean spreads produces a positive and significant estimate (estimate = 0.1880, t-statistic = 2.37). Given our findings in Table III that show that in the full specification, the natural log of mean spreads did not produce a reliable estimate, here we find that after orthogonalizing spread volatility to mean spreads, the coefficient on mean spreads is now positive and significant. Second, after controlling for these factors, we again find a positive and reliable estimate for $\sigma(SPRD_{i,t})^{\text{adj}}$ (estimate = 0.1728, t-statistic = 2.89). The results in Table V indicate that, after controlling for a variety of variables that influence next-month returns, the portion of spread volatility that is unrelated to mean spreads still contains predictability about future returns. These results contribute to our findings in Table III and suggest that there exists a return premium associated with spread volatility.

E. The Spread Volatility Return Premium and Controls for Other Measures of Liquidity Volatility

In this subsection, we continue to determine whether the return premium associated with spread volatility is robust to additional controls for other measures of liquidity volatility. In particular, we estimate the following equation using pooled stock-month data.

$$\begin{aligned} Ex - Ret_{i,t+1} = {} & \beta_0 + \beta_1 \sigma(SPRD)_{i,t} + \beta_2 \ln(SPRD_{i,t}) + \beta_3 Beta_{i,t} + \beta_4 \ln(Size_{i,t}) \\ & + \beta_5 \ln(B/M_{i,t}) + \beta_6 Ret_{i,t-6,t-1} + \beta_7 \ln(Turn_{i,t}) + \beta_8 \ln(Price_{i,t}) \\ & + \beta_9 Idiovolt_{i,t} + \beta_{10} \sigma(LIQUIDITY)_{i,t} + \varepsilon_{i,t+1}. \end{aligned} \tag{3}$$

The dependent variable and independent variables are similar to those in Equation (1). The only exception is that we include various measures of liquidity volatility—$\sigma(LIQUIDITY)_{i,t}$—which have been used in previous research. We have define $\sigma(LIQUIDITY)_{i,t}$ in three different ways. First, $\sigma(vol)_{i,t}$ is the natural log of the standard deviation of volume. Second, $\sigma(turn)_{i,t}$ is the natural log of the standard deviation of share turnover. Third, $\sigma(illiq)_{i,t}$ is the natural log of the standard deviation of Amihud's (2002) illiquidity. As before, we report t-statistics that are obtained using Newey-West (1987) standard errors with three lags.

Table VI reports the results from the Fama-MacBeth (1973) regressions from estimating equation (3). Column (1) shows the results when we include volume volatility. The control variables produce estimates that are qualitatively similar to those in previous tables. While $\sigma(vol_{i,t})$ does not produce a reliable estimate (estimate = 0.0578, t-statistic = 0.81), $\sigma(SPRD_{i,t})$ does (estimate = 0.2166, t-statistic = 4.28). In fact, similar results are found in Columns (2) and (3) when we include turnover volatility and illiquidity volatility, respectively. In both cases, $\sigma(SPRD_{i,t})$ produces a positive estimate that is reliably different from zero (estimates = 0.2174, 0.1955; t-statistics = 4.30, 3.49). In the full specification, we again find that the estimate on $\sigma(SPRD_{i,t})$ is positive and significant while the estimates on each of the other liquidity volatility measures are not statistically different from zero. The results in Table VI again support the presence of a return premium associated with spread volatility that is robust to controls for other measures of liquidity volatility.

F. The Spread Volatility Return Premium: A Multifactor Analysis

In this subsection, and those that follow, we continue our analysis by examining next-month returns across quintiles sorted by spread volatility. In particular, we sort the stock-month observations into quintiles based on $\sigma(SPRD)$ during month t and then report various measures of returns during month $t+1$. Table VII reports the results from this analysis. In Panel A, we report the results using all observations while Panels B and C show the results for the predecimalization and postdecimalization periods, respectively. Column (1) shows the results for next-month CRSP raw returns. Column (2) reports the abnormal return, which is the difference between CRSP raw returns and the value-weighted CRSP index. In Columns (3) to (5), we report the alphas from variants of the following equation.

$$Ret_{i,t} - Rf_t = \alpha + \beta_1(Rm_t - Rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t + \varepsilon_{i,t}. \tag{4}$$

Table VI. Fama-MacBeth Regressions

The table reports the results from estimating the following equation using Fama-MacBeth (1973) regressions.

$$Ex - Ret_{i,t+1} = \beta_0 + \beta_1\sigma(SPRD)_{i,t} + \beta_2 \ln(SPRD_{i,t}) + \beta_3 Beta_{i,t} + \beta_4 \ln(Size_{i,t}) + \beta_5 \ln(B/M_{i,t})$$
$$+ \beta_6 Ret_{i,t-6,t-1} + \beta_7 \ln(Turn_{i,t}) + \beta_8 \ln(\mathrm{Pr}ice_{i,t}) + \beta_9 Idiovolt_{i,t}$$
$$+ \beta_{10}\sigma(LIQUIDITY)_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is excess return or the difference between the raw return for stock i during month $t+1$ and the one-month T-Bill rate in month $t+1$. The independent variables include the following: $\sigma(SPRD_{i,t})$ is the standard deviation of the daily closing spreads for each stock i during month t; $\ln(SPRD_{i,t})$ is the natural log of average spreads for each stock i during month t. *Beta* is obtained from estimating a Capital Asset Pricing Model using daily returns, risk-free rates, and market returns using a rolling 6-month window; $\ln(Size_{i,t})$ is the market capitalization using shares outstanding and closing prices at the end of each month; $\ln(B/M_{i,t})$ is the natural log of the book-to-market ratio; $Ret_{i,t-6,t-1}$ is the cumulative return for stock i from month $t-6$ to $t-1$; $\ln(Turn_{i,t})$ is the natural log of share turnover; ln(*Price*) is the natural log of the CRSP closing price at the end of each month; *Idiovolt* is a measure of idiosyncratic volatility and is obtained by taking the standard deviation of the daily residual returns from a traditional four-factor model using a rolling 6-month window. We also include the standard deviations of various measures of liquidity $\sigma(LIQUIDITY)_{i,t}$, which we define three different ways. First, $\sigma(vol)_{i,t}$ is the natural log of the standard deviation of volume. Second, $\sigma(turn)_{i,t}$ is the natural log of the standard deviation of share turnover. And, third, $\sigma(illiq)_{i,t}$ is the natural log of the standard deviation of Amihud's (2002) illiquidity, which is the absolute value of the daily returns scaled by daily trade volume. We report t-statistics below each estimate that are obtained using Newey-West (1987) standard errors with three lags.

	All Observations			
	(1)	**(2)**	**(3)**	**(4)**
Intercept	1.8504***	1.8646***	2.0372***	1.9650***
	(3.03)	(3.05)	(3.27)	(3.12)
$\sigma(SPRD)_{i,t}$	0.2166***	0.2174***	0.1955***	0.1884***
	(4.28)	(4.30)	(3.49)	(3.32)
$\ln(SPRD_{i,t})$	0.0840	0.0840	0.0597	0.0684
	(0.95)	(0.95)	(0.66)	(0.76)
$Beta_{i,t}$	0.0150	0.0147	0.0113	0.0139
	(0.19)	(0.19)	(0.15)	(0.18)
$\ln(Size_{i,t})$	−0.0268	0.0295	0.0617	−1.8474
	(−0.31)	(0.71)	(1.31)	(−1.17)
$\ln(B/M_{i,t})$	0.2840***	0.2839***	0.2839***	0.2848***
	(5.21)	(5.21)	(5.21)	(5.25)
$Ret_{i,t-6,t-1}$	0.0115***	0.0115***	0.0115***	0.0115***
	(3.84)	(3.84)	(3.84)	(3.88)
$\ln(Turn_{i,t})$	0.0389	0.0456	0.1196	0.0919
	(0.35)	(0.41)	(1.53)	(0.70)
$\ln(Price_{i,t})$	−0.0898	−0.1468	−0.1410	1.7712
	(−0.65)	(−1.33)	(−1.26)	(1.14)
$IdioVolt_{i,t}$	−0.1465*	−0.1465	−0.1505*	−0.1497*
	(−1.72)	(−1.72)	(−1.77)	(−1.78)
$\ln(\sigma(Vol)_{i,t})$	0.0578			1.9167
	(0.81)	0.0507		(1.22)
$\ln(\sigma(Turn)_{i,t})$		(0.71)		−1.8820
			0.0423	(−1.20)
$\ln(\sigma(ILLIQ)_{i,t})$			(1.22)	0.0399
				(1.11)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table VII. Next-Month Returns across Spread Volatility Quintiles

The table reports various measures of next-month returns across quintiles sorted by spread volatility at the end of each month. Column (1) contains next-month CRSP *Raw Returns* while column (2) reports next-month *Abnormal Returns* across quintiles, which are calculated as the difference between raw returns and CRSP value-weighted market returns. In the last three columns, we estimate variants of the following equation and obtain the alphas.

$$Ret_{i,t} - R_{f,t} = \alpha + \beta_1(\mathrm{R}_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t + \varepsilon_{i,t}.$$

The dependent variable is the excess return or the difference between CRSP raw return and monthly risk free rate. The independent variables include the market risk premium ($R_{m,t} - R_{f,t}$), the small-minus-big factor (SMB_t), the high-minus-low factor (HML_t), the up-minus-down factor (UMD_t), and Pastor and Stambaugh's liquidity factor (LIQ_t). Column (3) reports the alpha obtained from estimating a Fama-French 3-Factor model in each quintile. Column (4) presents the alpha obtained from estimating a Fama-French-Carhart 4-Factor model in each quintile. Column (5) presents the alpha obtained from estimating a Fama-French-Carhart-Pastor-Stambaugh 5-Factor model in each quintile. Robust *t*-statistics are reported in parentheses.

	***Raw Returns* (1)**	***Abnormal Returns* (2)**	***FF3F Alpha* (3)**	***FF4F Alpha* (4)**	***FF5F Alpha* (5)**
			Panel A. All Observations		
Q I (Low)	0.0101	0.0070	0.0005	0.0009	0.0012
Q II	0.0103	0.0072	0.0005	0.0008	0.0010
Q III	0.0115	0.0084	0.0014	0.0021	0.0021
Q IV	0.0116	0.0086	0.0018	0.0028	0.0023
Q V (High)	0.0120	0.0090	0.0038	0.0051	0.0055
Q V – Q I	0.0019***	0.0020***	0.0033***	0.0042***	0.0043***
	(4.32)	(4.71)	(9.60)	(12.07)	(11.39)
			Panel B. 1993 to 2000 (Predecimalization)		
Q I (Low)	0.0130	0.0071	−0.0007	−0.0001	0.0006
Q II	0.0111	0.0052	−0.0021	−0.0010	−0.0004
Q III	0.0122	0.0063	−0.0012	0.0008	0.0007
Q IV	0.0118	0.0060	−0.0007	0.0020	0.0022
Q V (High)	0.0138	0.0080	0.0026	0.0059	0.0063
Q V – Q I	0.0008	0.0009	0.0033***	0.0060***	0.0057***
	(1.11)	(1.37)	(5.95)	(10.45)	(9.58)
			Panel C. 2001 to 2012 (Postdecimalization)		
Q I (Low)	0.0072	0.0069	0.0019	0.0019	0.0016
Q II	0.0094	0.0091	0.0024	0.0024	0.0021
Q III	0.0108	0.0105	0.0031	0.0032	0.0033
Q IV	0.0114	0.0110	0.0035	0.0036	0.0023
Q V (High)	0.0103	0.0099	0.0040	0.0042	0.0044
Q V – Q I	0.0031***	0.0030***	0.0021***	0.0023***	0.0028***
	(5.27)	(5.67)	(4.89)	(5.35)	(5.76)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Equation (4) is a common five-factor model, where risk factors are the market risk premium from the standard CAPM, the Fama and French (1996) small-minus-big (*SMB*) factor, the Fama and French (1996) high-minus-low (*HML*) factor, the Carhart (1997) up-minus-down (*UMD*) factor, and the Pastor and Stambaugh (2003) liquidity risk (*LIQ*) factor. After sorting stocks into quintiles based on $\sigma(SPRD_{i,t})$ during the previous month, we estimate variants of Equation (4) and report the estimated alphas across each quintile. Column (3) shows the estimated alpha for the Fama-French 3-Factor regressions (*FF3F Alpha*) while Columns (4) and (5) report the estimated alpha for the Carhart 4-Factor regressions (*FF4F Alpha*) and the Pastor-Stambaugh 5-Factor regressions (*FF5F Alpha)*, respectively.

Column (1) shows that next-month raw returns are monotonically increasing across increasing spread volatility quintiles. In the quintile with the largest spread volatility, next-month raw returns are 1.2%. The difference between extreme quintiles is 0.19% and is statistically different from zero. Said differently, stocks in the largest spread volatility quintile outperform stocks in the smallest spread volatility quintile by 0.19% per month. In economic terms, this difference is similar to magnitude of the return premium found in our Fama-MacBeth (1973) regressions. Results in Column (2) are qualitatively similar to those in Column (1).

Column (3) reports the next-month *FF3F Alpha* across quintiles sorted by spread volatility. Again, we find that these alphas are generally increasing across quintiles. After controlling for the risk factors described in Fama and French (1996), we find that stocks in the highest spread volatility quintile produce an alpha of 0.38% per month, which is both statistically and economically significant. For example, the 38 basis point monthly return premium corresponds to 4.56% in annual terms. The difference in alphas between extreme quintiles is 0.33%, which is statistically different from zero (t-statistic $= 9.60$). We are able to make similar inferences when examining *FF4F Alphas* in Column (4). However, we recognize the need to control for the Pastor-Stambaugh liquidity risk factor since our measure of spread volatility could just be a proxy for liquidity risk. Column (5) reports the alphas from the five-factor model. In general, the results are similar to those in previous columns. Stocks in the quintile with the highest spread volatility have statistically and economically significant five-factor alphas. Although the five-factor alphas are not monotonically increasing in quintiles I and II, the results in Table VII provide further evidence of a significant return premium associated with spread volatility.

When looking at the predecimalization period in Panel B, we find results that are generally similar to those found in Panel A. We do note, however, a few exceptions. In both Columns (1) and (2), we do not find that the difference between extreme quintiles is statistically different from zero. However, Columns (3) to (5), which report alphas for more traditional multifactor models indeed show that alphas are generally increasing across quintiles and that the difference between extreme quintiles is reliably different that zero. In fact, the magnitude of these differences in the latter columns is slightly greater than the magnitude of the differences in the corresponding columns in Panel A. Panel C presents the results for the postdecimalization period. In each case, we find that next-month returns are monotonically increasing across spread volatility quintiles. Differences between extreme quintiles are positive and significant in each column. In economic terms, the difference in Column (5) suggests that the return premium associated with spread volatility is approximately 3.4% in annual terms.

G. The Spread Volatility Return Premium: Double Sorts by Other Measures of Liquidity

We continue our investigation into the spread volatility premium by conducting a series of double-sorts. Table VIII shows five-factor alphas across double-sorted quintiles—first by spread

Table VIII. Multifactor Alphas across Two-Way Liquidity Sorts

The table reports five-factor alphas across quintiles across double-sorted quintiles. We first sort first by spread volatility and then by four measures of liquidity, which have been defined previously (*SPRD*, *Turn*, *Volume*, and *Illiq*), in each of the four panels.

$$Ret_{i,t} - R_{f,t} = \alpha + \beta_1(\mathrm{R}_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t + \varepsilon_{i,t}.$$

The dependent variable is the excess return or the difference between CRSP raw return and monthly risk free rate. The independent variables include the market risk premium ($R_{m,t} - R_{f,t}$), the small-minus-big factor (SMB_t), the high-minus-low factor (HML_t), the up-minus-down factor (UMD_t), and Pastor and Stambaugh's liquidity factor (LIQ_t). Column (3) reports the alpha obtained from estimating a Fama-French 3-Factor model in each quintile. Robust *t*-statistics are reported in parentheses.

	Q I (Low) (1)	Q II (2)	Q III (3)	Q IV (4)	Q V (High) (5)	Q V – Q I (6)
Panel A. First Sort by σ (SPRD), Second Sort by SPRD						
Q I (Low)	0.0036	0.0009	0.0021	0.0003	−0.0004	−0.0040***
						(−4.48)
Q II	0.0003	0.0017	0.0016	0.0007	0.0022	0.0019**
						(2.18)
Q III	0.0011	0.0014	0.0035	0.0024	0.0046	0.0035***
						(4.20)
Q IV	−0.0007	0.0000	0.0008	0.0034	0.0069	0.0076***
						(9.76)
Q V (High)	0.0016	0.0010	0.0026	0.0048	0.0144	0.0128***
						(15.53)
Q V – Q I	−0.0020***	0.0001	0.0005	0.0045***	0.0148***	0.0168***
	(−3.26)	(0.15)	(0.70)	(6.16)	(17.95)	(20.38)
Panel B. First Sort by σ SPRD), Second Sort by Volume						
Q I (Low)	0.0015	0.0018	0.0032	0.0046	0.0121	0.0106***
						(16.50)
Q II	0.0009	0.0014	0.0029	0.0036	0.0076	0.0067***
						(9.38)
Q III	0.0023	0.0005	0.0018	0.0032	0.0045	0.0022***
						(2.77)
Q IV	0.0002	0.0010	0.0019	0.0017	0.0034	0.0032***
						(3.52)
Q V (High)	0.0032	0.0005	0.0009	−0.0014	0.0002	−0.0030***
						(−2.86)
Q V – Q I	0.0017**	−0.0013	−0.0023**	−0.0060***	−0.0119***	−0.0136***
	(2.38)	(−1.54)	(−2.50)	(−6.08)	(−11.36)	(−12.98)
Panel C. First Sort by σ (SPRD), Second Sort by Turn						
Q I (Low)	0.0021	0.0011	0.0025	0.0025	0.0086	0.0065***
						(9.86)
Q II	0.0010	0.0012	0.0029	0.0029	0.0061	0.0051***
						(7.21)
Q III	0.0009	0.0001	0.0014	0.0027	0.0042	0.0033***
						(6.41)
Q IV	−0.0005	0.0006	0.0011	0.0029	0.0059	0.0064***
						(6.96)
Q V (High)	0.0025	0.0022	0.0027	0.0006	0.0030	0.0005
						(0.48)
Q V – Q I	0.0004	0.0011	0.0002	−0.0019*	−0.0056***	−0.0060***
	(0.45)	(1.15)	(0.20)	(−1.80)	(−5.32)	(−5.70)

(*Continued*)

Table VIII. Multifactor Alphas across Two-Way Liquidity Sorts (*Continued*)

	Q I (Low) (1)	Q II (2)	Q III (3)	Q IV (4)	Q V (High) (5)	Q V – Q I (6)
			Panel D. First Sort by σ (SPRD), Second Sort by Illiquidity			
Q I (Low)	0.0027	0.0016	0.0018	0.0003	0.0017	−0.0010
						(−1.07)
Q II	0.0013	0.0003	0.0019	0.0020	0.0013	0.0000
						(0.03)
Q III	0.0005	0.0019	0.0022	0.0010	0.0037	0.0032***
						(3.95)
Q IV	0.0003	0.0008	0.0021	0.0036	0.0078	0.0075***
						(10.13)
Q V (High)	0.0011	0.0005	0.0028	0.0047	0.0134	0.0123***
						(16.16)
Q V – Q I	−0.0016***	−0.0011*	0.0010	0.0044***	0.0117***	0.0133***
	(−2.64)	(−1.76)	(1.54)	(6.72)	(15.38)	(17.48)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

volatility, second by other measures of liquidity.[6] Panel A shows the results when the second sort is by mean spreads while Panels B though D present our findings when the second sort is volume, turnover, and Amihud's (2002) illiquidity. In this table, and those that follow, the first sort is reported across rows, while the second sort is reported down each column. Therefore, when we attempt to determine how the spread volatility premium interacts with mean spreads, we can focus on column (6) that shows high-minus low differences in spread volatility quintiles across mean spread quintiles. Focusing on column (6), we find that the return premium associated with spread volatility is monotonically increasing across mean spread quintiles. The difference between extreme mean spread quintiles is 0.0168 (t-statistic = 20.38), suggesting that the spread volatility premium is directly related to the size of mean spreads. To the extent that mean spreads properly approximate liquidity inversely, our findings in Panel A seem to indicate that the spread volatility premium is greatest for the least liquid stocks.

Panels B and C show the results when the second sort is volume and turnover, respectively. Given that the conclusions are similar between these two panels, we will only discuss our findings generally. As seen in column (6) of either panel, we find that the difference between extreme spread volatility quintiles is generally decreasing across increasing volume/turnover quintiles. The difference-in-differences (row 6 of Column 6) is negative and reliably different than zero in both panels. These results suggest that the spread volatility premium is driven by stocks with the least volume/turnover. Again, to the extent that volume/turnover is a direct proxy for liquidity, our findings in these panels indicate that the return premium associated with spread volatility is driven by the least liquid stocks.

Panel D shows the results when the second sort is Amihud's (2002) measure of illiquidity. Under the assumption that illiquidity is measuring liquidity inversely, we expect to observe the

[6] In a series of unreported tests, we conduct reverse double-sorted portfolios and sort first by the measures of liquidity and then by spread volatility. The conclusions that we are able to draw are qualitatively similar to those in this article. These unreported results are available upon request.

spread volatility premium to increase across illiquidity quintiles. Column (6) of Panel D presents our findings, which are consist with our expectation. This column shows that the difference in five-factor alphas between extreme spread volatility quintiles is increasing monotonically across illiquidity quintiles. The difference-in-difference is positive and statistically significant. Again, these results support the idea that the return premium associated with spread volatility is driven by the least liquid stocks.

We continue our analysis by constructing double-sorted quintiles where the second sort consists of other stock characteristics (market cap, book-to-market ratios, and idiosyncratic volatility). While the tests in Table VIII were conducted to identify whether the spread volatility return premium is driven by illiquid stocks, these tests attempt to determine whether the return premium is related to the size premium, the value premium, and idiosyncratic volatility. Table IX presents five-factor alphas across these double-sorted quintiles.

For brevity, we again focus our discussion on column (6) of each panel. This column shows differences in alphas between extreme spread volatility quintiles across quintiles sorted by the various stock characteristics. Panel A shows that the Q V − Q I difference in five-factor alphas are decreasing across increasing size quintiles—although not monotonically. Further, the largest differences are in the smallest-cap stocks suggesting that the return premium associated with spread volatility is driven by the smallest stocks. This finding should not come as surprise given our findings in the previous table and the results in Table II that suggest that small-cap stocks are the least liquid. Observing a return premium in the smallest stocks might simply be identifying the relationship between the return premium and illiquidity, which was found in the previous table. We recognize, however, that other explanations exist. For instance, small stocks are likely to have more information asymmetry and when investors face this asymmetry generally they may become more concerned with other types of uncertainty, like liquidity uncertainty, and therefore may only purchase these types of stocks at a significant discount.

Panel B shows the results when the second sort is by book-to-market ratios. Again, focusing on column (6), we find that the return premium associated with spread volatility is generally increasing across stocks with the highest book-to-market ratios. These findings are consistent with the idea that the spread volatility premium is driven by value stocks. Table II reports that mean spreads are directly related to book-to-market ratios, so again, it is possible that these results are simply capturing the relation between the return premium and less liquid stocks.

Panel C presents the double-sorted five-factor alphas when the second sort is idiosyncratic volatility. Perhaps spread volatility is simply capturing some sort of price volatility. In Panel C, column (6), however, we do not find a particular pattern in the return premium across idiosyncratic volatility quintiles. While the differences between extreme spread volatility quintiles is positive and statistically significant in each quintile, the difference-in-difference (row 6, column 6) is only marginally significant. These results seem to suggest that the return premium associated with spread volatility is not related to idiosyncratic volatility.

In our final set of tests, we examine five-factor alphas across double-sorted portfolios where the second sort consists of the three other measures of liquidity volatility. Table X shows the five-factor alphas obtained from estimating Equation (4). Panel A shows the alphas when the second sort is by volume volatility. As before, we focus on column (6), which provides the difference between extreme spread volatility quintiles or the spread volatility return premium. Interestingly, we find that the return premium in column (6) is decreasing monotonically across quintile sorts

Table IX. Multifactor Alphas across Two-Way Stock Characteristic Sorts

The table reports five-factor alphas across quintiles across double-sorted quintiles. We first sort first by spread volatility and then by three other stock characteristics, which have been defined previously ($Size_{i,t}$, $B/M_{i,t}$, and $IdioVolt_{it}$), in each of the three panels.

$$Ret_{i,t} - R_{f,t} = \alpha + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t + \varepsilon_{i,t}.$$

The dependent variable is the excess return or the difference between CRSP raw return and monthly risk free rate. The independent variables include the market risk premium ($R_{m,t} - R_{f,t}$), the small-minus-big factor (SMB_t), the high-minus-low factor (HML_t), the up-minus-down factor (UMD_t), and Pastor and Stambaugh's liquidity factor (LIQ_t). Column (3) reports the alpha obtained from estimating a Fama-French 3-Factor model in each quintile. Robust *t*-statistics are reported in parentheses.

	Q I (Low) (1)	Q II (2)	Q III (3)	Q IV (4)	Q V (High) (5)	Q V – Q I (6)
Panel A. First sort by σ (SPRD), Second Sort by Mkt Cap						
Q I (Low)	0.0018	0.0027	0.0036	0.0059	0.0127	0.0109***
						(12.83)
Q II	−0.0005	0.0013	0.0025	0.0037	0.0070	0.0075***
						(9.46)
Q III	0.0010	0.0013	0.0016	0.0018	0.0047	0.0037***
						(4.46)
Q IV	0.0031	0.0003	0.0012	−0.0006	0.0024	−0.0007
						(−0.78)
Q V (High)	0.0006	−0.0004	0.0017	0.0008	0.0009	0.0003
						(0.36)
Q V – Q I	−0.0012**	−0.0031***	−0.0019***	−0.0051***	−0.0118***	−0.0106***
	(−2.34)	(−5.01)	(−2.79)	(−6.80)	(−14.03)	(−12.60)
Panel B. First Sort by σ (SPRD), Second Sort by B/M						
Q I (Low)	−0.0003	−0.0049	−0.0060	−0.0082	−0.0077	−0.0074***
						(−7.06)
Q II	−0.0001	−0.0009	0.0016	0.0002	0.0038	0.0039***
						(4.56)
Q III	0.0003	0.0010	0.0036	0.0043	0.0064	0.0061***
						(8.27)
Q IV	0.0019	0.0038	0.0045	0.0060	0.0126	0.0107***
						(14.95)
Q V (High)	0.0041	0.0059	0.0070	0.0093	0.0125	0.0084***
						(10.55)
Q V – Q I	0.0044***	0.0108***	0.0130***	0.0175***	0.0202***	0.0158***
	(7.91)	(17.49)	(19.03)	(23.56)	(25.36)	(19.84)
Panel C. First Sort by σ (SPRD), Second Sort by IdioVolt						
Q I (Low)	0.0024	0.0029	0.0039	0.0046	0.0038	0.0012**
						(2.11)
Q II	0.0007	0.0016	0.0024	0.0025	0.0048	0.0041***
						(5.94)
Q III	−0.0000	0.0001	0.0026	0.0030	0.0063	0.0063***
						(8.05)
Q IV	0.0004	0.0001	0.0028	0.0023	0.0070	0.0066***
						(7.33)
Q V (High)	0.0025	0.0005	−0.0011	−0.0008	0.0057	0.0031***
						(2.73)
Q V – Q I	0.0001	−0.0024**	−0.0050***	−0.0054***	0.0019*	0.0019*
	(0.11)	(−2.35)	(−4.60)	(−4.74)	(1.67)	(1.68)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table X. Multifactor Alphas across Two-Way Liquidity Volatility Sorts

The table reports five-factor alphas across quintiles across double-sorted quintiles. We first sort first by spread volatility and then by three measures of liquidity volatility, which have been defined previously ($\sigma(Vol)_{i,t}$, $\sigma(Turn)_{i,t}$, and $\sigma(Illiq)_{i,t}$), in each of the three panels.

$$Ret_{i,t} - R_{f,t} = \alpha + \beta_1(\mathrm{R}_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t + \varepsilon_{i,t}.$$

The dependent variable is the excess return or the difference between CRSP raw return and monthly risk free rate. The independent variables include the market risk premium ($R_{m,t} - R_{f,t}$), the small-minus-big factor (SMB_t), the high-minus-low factor (HML_t), the up-minus-down factor (UMD_t), and Pastor and Stambaugh's liquidity factor (LIQ_t). Column (3) reports the alpha obtained from estimating a Fama-French 3-Factor model in each quintile. Robust *t*-statistics are reported in parentheses.

	Q I (Low) (1)	Q II (2)	Q III (3)	Q IV (4)	Q V (High) (5)	Q V – Q I (6)
Panel A. First Sort by σ(SPRD), Second Sort by σ(Vol)$_{i,t}$						
Q I (Low)	0.0014	0.0018	0.0034	0.0047	0.0116	0.0102***
						(15.75)
Q II	0.0003	0.0005	0.0024	0.0025	0.0067	0.0064***
						(8.79)
Q III	0.0002	0.0010	0.0022	0.0034	0.0053	0.0051***
						(6.35)
Q IV	0.0009	−0.0001	0.0019	0.0019	0.0019	0.0010
						(1.09)
Q V (High)	0.0031	0.0018	0.0008	−0.0008	0.0023	−0.0008
						(−0.77)
Q V − Q I	0.0016**	0.0000	−0.0026***	−0.0055***	−0.0093***	−0.0110***
	(2.17)	(0.05)	(−2.83)	(−5.59)	(−8.96)	(−10.60)
Panel B. First Sort by σ(SPRD), Second Sort by *σ(Turn)$_{i,t}$*						
Q I (Low)	0.0014	0.0013	0.0024	0.0020	0.0070	0.0056***
						(8.30)
Q II	0.0015	0.0005	0.0022	0.0028	0.0044	0.0029***
						(3.98)
Q III	−0.0004	0.0004	0.0015	0.0015	0.0055	0.0059***
						(7.27)
Q IV	0.0013	0.0003	0.0014	0.0034	0.0066	0.0053***
						(5.77)
Q V (High)	0.0022	0.0027	0.0031	0.0020	0.0041	0.0019*
						(1.85)
Q V − Q I	0.0008	0.0014	0.0007	−0.0000	−0.0029***	−0.0037***
	(0.93)	(1.49)	(0.71)	(−0.05)	(−2.82)	(−3.60)
Panel C. First Sort by σ(SPRD), Second Sort by *σ(Illiq)$_{i,t}$*						
Q I (Low)	0.0024	0.0010	0.0012	−0.0001	0.0010	−0.0014
						(−1.50)
Q II	0.0016	0.0008	0.0017	0.0025	0.0017	0.0001
						(0.11)
Q III	0.0006	0.0020	0.0030	0.0011	0.0043	0.0037***
						(4.61)
Q IV	0.0003	0.0008	0.0014	0.0031	0.0082	0.0079***
						(10.93)
Q V (High)	0.0010	0.0004	0.0032	0.0050	0.0126	0.0116***
						(15.14)
Q V − Q I	−0.0014**	−0.0006	0.0020***	0.0051***	0.0116***	0.0130***
	(−2.33)	(−0.97)	(3.10)	(7.77)	(15.14)	(16.97)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

suggesting that the return premium associated with spread volatility is driven by stocks with the least volume volatility. These findings seem to suggest that spread volatility and volume volatility are not necessarily capturing the same type of illiquidity.

In Panel B, we do not find a monotonic pattern for the return premium across turnover volatility quintiles. There is some evidence that the return premium is weakest in stocks with the highest turnover volatility. The difference-in-difference is negative and significant. These findings provide some support for our results in Panel A and suggest that, if anything, the return premium associated with spread volatility is not driven by stocks with the highest turnover volatility.

Panel C presents the five-factor alphas across double-sorted portfolios where the second sort is based on the volatility of illiquidity. In this panel, we find that the return premium in column (6) is increasing monotonically across increasing illiquidity volatility quintiles. The difference-in-difference is positive and significant suggesting that the spread volatility premium is highest among stocks with the highest volatility of Amihud's (2002) illiquidity.

The results in Tables VIII through X allow for some important inferences. First, the return premium that has been documented in earlier tables is strongest among stocks that are least liquid, small-cap stocks, and value stocks. We do not find that the return premium is explained by idiosyncratic volatility. Further, Table X seems to indicate that the volatility of trading activity (volume and turnover) is capturing something different than the volatility of bid-ask spreads as the return premium associated with spread volatility is greatest among stocks with the least volatility of trading activity. However, we do find strong evidence that the return premium is driven by stocks with high illiquidity volatility.

H. Additional Robustness Tests

In this section we describe a number of additional tests that we do not report in this paper, but discuss below. First, we replicate Tables VIII to X, but conduct reverse double sorts, where spread volatility is the second sort in each case. The conclusions that we are able to draw in these unreported tests are similar to those in this article. That is, the spread volatility return premium is driven by the least liquid stocks, stocks with the lowest volatility of trading activity, and stocks with the highest volatility in Amihud's (2002) measure of illiquidity.

We also recognize that sorting into finer quantiles might provide an important story. We therefore sort stocks into deciles instead of quintiles and still find that next-month returns are highest in the highest spread volatility decile. Further, we find that next-month returns are generally increasing across increasing deciles. We choose to report the quintile sorts since double-sorted deciles become difficult to tabulate.

We also recognize the possibility that the number of restrictions on the data might introduce nonrandomness to our sample. We replicate much of our analysis after imposing each one of the several restrictions to the data. We are able to find that the conclusions we draw in this paper hold when imposing each of these data restrictions.

III. Conclusion

While the importance of liquidity in financial markets is well documented, the relative importance of the different dimensions of liquidity is not as clear. In this paper, we examine the relation between liquidity risk or uncertainty about future liquidity and future returns. We use the volatility of bid-ask spreads as our proxy for liquidity risk and find that it is associated with a large premium in expected stock returns. In general, we find that the return premium associated with spread volatility is statistically significant and economically meaningful. We examine the relation between future returns and spread volatility by estimating Fama-MacBeth regressions and find that spread volatility has explanatory power for future returns after controlling for mean bid-ask spreads as well as several other factors that might influence future returns. We also estimate more traditional multifactor asset pricing models and find that the alphas obtained from these models are increasing across stocks sorted by spread volatility.

This significant return premium is robust to different tick-size regimes. We also show that the spread volatility premium is not fully explained by the more traditional relation between mean spread and future returns. Additional robustness tests reveal that the spread volatility return premium is robust to other measures of liquidity volatility and is related to market cap, book-to-market ratios, but unrelated to idiosyncratic volatility.

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