Volatility, Liquidity, and Liquidity Risk*

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This Draft: October 15, 2016
First Draft: February 17, 2015

Abstract

Liquidity affects various capital market outcomes such as expected returns and capital structure. Prior research has shown that an important determinant of liquidity is volatility, where higher stock return volatility is associated with higher illiquidity. Using recent developments in the literature, we revisit this relation and decompose total volatility into its jump and diffusive components and argue that the two volatility components are predicted to have different effects on liquidity. This decomposition is motivated by the fact that variation in the structure of volatility across firms is driven by variation in information environments. This raises a new unexplored channel, independent of information asymmetry and total volatility, through which the information environment can shape liquidity. We find that the positive relation between total volatility and illiquidity is exclusively driven by the jump component, and is independent of any information asymmetry effects. In contrast, we find a negative relation between diffusive volatility and illiquidity. We show that this negative relation is driven by the positive association between diffusive volatility and trading activity. Finally, we show that these findings translate to differential effects on liquidity risk and premium for the jump and diffusive volatility components. Our findings have implications for the understanding of asset prices, corporate finance decisions and policy-makers.

*We are grateful for insightful comments and suggestions from Yakov Amihud, Larry Glosten, Koresh Galil, Gur Huberman, Alon Kalay, Mattia Landoni, Gil Sadka, Ronnie Sadka, Amnon Schreiber and Zvi Wiener. We also thank seminar participants at Bar-Ilan University, Ben-Gurion University, IDC Herzliya, and Yale University, and conference participants at the 2015 IEA meetings in Tel Aviv and the 2016 IRMC meetings in Jerusalem for helpful remarks. Finally, we thank Dan Mechanic, Benny Chang, Sangho Kim and Charles Tang for their assistance with the TAQ data.

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1 Introduction

Stock liquidity and its variation affect a number of capital market outcomes such as expected returns (e.g., Amihud and Mendelson, 1986 and 2015; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005), capital structure (e.g., Lipson and Mortal, 2009), dividend policy (Banerjee et al., 2007), and ownership structure (e.g., Bhide, 1993). Given these important implications, numerous theoretical and empirical studies have investigated the determinants of liquidity and demonstrated the role stock return volatility plays in driving illiquidity (e.g., Stoll, 1978a; Stoll 1978b; Stoll 2000; Amihud and Mendelson, 1989; Bao and Pan, 2013).

However, treating volatility as a uniform measure with a homogeneous impact on liquidity overlooks the subtle, yet potentially important, structure of total volatility. More recent developments in the asset pricing literature treat stock returns as a jump-diffusion process, that is, as a combination of a continuous Brownian motion component and a discontinuous jump component. Consequently, this approach implies that the total return variance is an aggregate outcome of two separate sources that have very different characteristics. While volatility patterns generated by a discontinuous jump process arise from infrequent, large, isolated price changes, the diffusive volatility arises from smooth, continuous, small price changes. The overall volatility is merely the integration of these two types of volatility.

The decomposition of total volatility into its jump and diffusive components is not a mere "technical" exercise, but is motivated by an important economic reasoning. Each volatility component is driven by different economic forces related to the rate of information arrival. Stocks for which information flows in a smoother and more continuous way are more likely to be governed by a diffusive process. On the other hand, stocks for which information arrives in a bulky, discontinuous way are more likely to be subject to jumps (e.g., Maheu and McCurdy, 2004). The rate of information arrival for each firm is determined by its information environment which is governed by various factors, such as the disclosure regulations that applies to it, its voluntary disclosure policy, and its level of analysts coverage.\(^1\)

Relating the firm’s information environment to capital market outcomes has been a central theme in the literature that examines the role of information in capital markets. Numerous studies in accounting and finance emphasized its importance to liquidity and liquidity driven

\(^1\)In a companion study we confirm this intuition by showing that issuing management forecasts, increasing their number, and having greater analyst coverage all reduce jump volatility. Moreover, following Kelly and Ljungqvist (2012), we use drops in analyst coverage as a result of an exogenous brokerage house closures to show that a reduction in analyst coverage causally increases jump volatility. The results of the companion study are replicated in the sample of the current study and provided in Appendix A.
outcomes (e.g., Kelly and Ljungqvist, 2012; Balakrishnan, Billings, Kelly, and Ljungqvist, 2014). However, the information environment can give rise to multiple channels that shape liquidity, where the existing literature has so far focused on the channels of information asymmetry and total volatility.

We emphasize a new unexplored channel through which the information environment can shape liquidity and liquidity driven expected returns. We highlight that the information environment also works through the structure of volatility to shape liquidity and liquidity driven outcomes, independently of the already explored channels of information asymmetry and total volatility. The information environment determines the pace at which information arrives to the market and, consequently, affects the relative dominance of the jump versus the diffusive component of volatility. Hence, as we argue in this paper, since each volatility component impacts liquidity differently, firms with different information environments are likely to have different levels of liquidity. That is, even in the absence of any differences in information asymmetry or total volatility across firms, differences in their information environments can still affect liquidity differently through their effect on the structure of volatility. Moreover, this channel implies that differences in information environments create differences in liquidity even in the absence of any information asymmetry at all.

The literature on jumps has highlighted two facts that lead to differential predictions for each volatility component on liquidity. These facts are directly linked to the theory of liquidity, which emphasizes the risks market makers face in determining liquidity. The first fact is that jumps in prices are difficult to hedge, unlike diffusive changes (e.g., Garleanu et al., 2009). Market-makers bear the risk of price changes to their stock inventories, which they must maintain. Therefore, bid-ask spreads are set to compensate them for bearing this inventory risk (e.g., Stoll 1978a; Amihud and Mendelson, 1980; Ho and Stoll, 1981; Ho and Stoll, 1983). In a diffusive environment market-makers can control their potential losses, update their inventory portfolios, and fix "stop-loss" rules in a more flexible and gradual manner compared to a trading environment that exhibits infrequent dramatic price changes. That is, jumps impose a more restrictive set of risk management tools and stopping rules compared to diffusive price changes.

Similarly, to reduce inventory risk, market-makers often hedge their inventories with correlated instruments, such as options and other correlated stocks or ETFs. Therefore, it is

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2 In this study we do not aim to establish a causal link between information environment, jump volatility, liquidity and liquidity risk. We take the more modest goal of being the first to document these associations. Any use of causal terms throughout the paper is motivated only by the theoretical arguments stated in the introduction and should not be treated in the strict econometric sense.

3 See Longstaff (1995, 2014), who models the implications of a similar aspect to illiquidity.
mainly the non-hedgeable portion of their inventory that drives their compensation in the form of bid-ask spreads (e.g., Benston and Hagerman 1974; Ho and Stoll, 1983; Froot and Stein 1998; Naik and Yadav, 2003a; Naik and Yadav, 2003b). Jump risk, as a discontinuous price change, cannot be easily hedged away, as dynamic replicating strategies become infeasible under incomplete markets (e.g., Garleanu et al., 2009; Jameson and Wilhelm, 1992; Gromb and Vayanos, 2002; Chen et al., 2014). Therefore, as the non-hedgeable portion of total volatility, it is the jump-driven component that market-makers are likely to demand compensation for.

The second fact is that diffusive volatility is associated with increased trading, while jump volatility is not (e.g., Giot et al., 2010). Higher turnover rates reduce market-makers’ inventory costs and therefore increase liquidity (Stoll 1978a). This line of reasoning entails a negative association between diffusive volatility and illiquidity through turnover.

Taken together, these reasons suggest a positive relation between jump volatility and illiquidity, while a weaker relation, or even a negative one, is expected between diffusive volatility and illiquidity.

To address these predictions, we follow standard methodologies implemented and validated by Ait-Sahalia (2004) and others to fit a log-normal jump-diffusion process to all stocks listed on the NYSE and NASDAQ from 2002-2011. We estimate the parameters of the jump and diffusive processes, measure total return variance, and disentangle the respective contribution of the jump and diffusive volatility components to total variance. As Ait-Sahalia (2004) points out, this methodology can perfectly disentangle the diffusive and jump components. Then, using Fama-MacBeth regressions we test for the potential impact each class of volatility has on bid-ask spreads.

We find that the relation between volatility and bid-ask spreads is exclusively driven by the jump component. These results are independent of any information asymmetry effects as they are maintained in all levels of information asymmetry and remain robust to the inclusion of a proxy for information asymmetry as a control variable. In contrast, we show that the diffusive component is negatively associated with illiquidity. Gauging the economic magnitude of their effects, an increase of one standard deviation in the jump-driven volatility component increases bid-ask spreads by approximately 30 basis points, whereas an equivalent increase in the diffusive volatility component decreases bid-ask spreads by approximately 10 basis points. We show that this negative association is fully driven by the relation between

\[^4\]Inferences throughout this paper remained qualitatively the same when we used the Amihud (2004) illiquidity measure instead of bid-ask spreads.
diffusive volatility and turnover. After accounting for trading activity, diffusive volatility has negligible economic effects. Finally, we show that our results are unlikely to be driven by reverse causality. Since our findings are maintained at all levels of turnover, it is unlikely that merely thin trading fully drives our findings.

One possible implication of the differential results that each liquidity component has on liquidity, is that it may also carry over to liquidity risk and liquidity risk premiums. A number of studies (e.g., Pastor and Stambaugh, 2003; Sadka, 2006) have shown that liquidity risk is priced. These studies show how stock liquidity is sensitive to aggregate market liquidity and market performance. Therefore, investors demand higher risk premiums for stocks that suffer from greater illiquidity in times of stress, times in which they also exhibit large losses in wealth. In the context of our analysis, since the jump-volatility component is the dominant driver behind illiquidity, it is possible it would also be the main driver determining liquidity risk and liquidity risk premiums.

We find that the jump volatility component has a positive and statistically significant effect for various measures of liquidity risk. On the other hand, the diffusive component has a negative effect on liquidity risk. That is, only jump volatility increases liquidity risk while diffusive volatility does not. Furthermore, following the methodology of Pastor and Stambaugh (2003), we show that only the jump volatility component increases the priced liquidity risk.

Our study contributes to several streams of literature. First, our study contributes to the understanding of the economic forces behind illiquidity. Although prior literature emphasized the importance of information environment to liquidity (e.g., Kelly and Ljungqvist, 2012; Balakrishnan et al., 2014), we are the first to document its effect through the structure of volatility. Relatedly, our findings suggest that firms can improve their liquidity and cost of capital if they are able to enhance their information environment in a way that reduces jump volatility.\footnote{This yields a change in equilibrium as there are likely significant costs for enhancing the information environment.} Second, our study contributes to the literature that studies the determinants of liquidity, particularly that which documents the relation between volatility and liquidity (Stoll, 1978a; Stoll 1978b; Stoll 2000; Amihud and Mendelson, 1989). Our study enhances this literature by being the first to document that the structure of volatility matters for illiquidity in addition to raw levels of volatility. Third, our study contributes to the literature that studies the consequences of jumps to a variety of financial variables. This literature documented that jump and diffusion processes have very different effects on credit risk (e.g., Zhou 2001; Cremers, Driessen and Maenhout 2008), on market beta (e.g.,}
Todorov and Bollerslev 2010; Cremers, Halling and Weinbaum 2015; Bollerslev, Li, and Todorov 2016), and on stock option pricing (e.g., Duffie, Pan and Singleton 2000; Pan 2002; Garleanu, Pederson and Poteshman 2009). Our study adds to this literature by providing evidence that the jump and diffusive components of volatility have very different effects on liquidity. Fourth, our study contributes to the literature on liquidity risk (e.g., Pastor and Stambaugh, 2003) by showing that the jump and diffusive effects on liquidity also carry over to liquidity risk and premiums.

Moreover, our findings also have regulatory implications to security markets. Our results show that implementing accounting policies that encourage more continuous information disclosure may help increase liquidity. These considerations are relevant to reforms currently being implemented to the regulatory environment in the EU. The European Commission recently removed the obligation to publish interim management statements and announced its intention to abolish quarterly financial reports for publicly traded companies, steps that might have important consequences to liquidity. More generally policies that increase the continuous stream of information to the markets (e.g., enhanced media coverage, social media discussions) and price informativeness are likely to improve the diffusion component of volatility and improve liquidity.

The remainder of this paper is organized as follows. In the next section we describe our methodology and empirical approach followed by our data sources and descriptive statistics. Sections 5 describes our results and discusses additional robustness tests. Implications to liquidity risk and premium are addressed in Section 6 and Section 7 concludes.

2 Methodology

2.1 Model Description and Calibration

In our analysis, we follow a standard framework for modeling jump-diffusion processes and apply estimation procedures that were used, validated and empirically tested in numerous studies (e.g., Ait-Sahalia, 2004; Yu, 2007). Following Merton (1976), we assume a continuous trading market for a stock with price \( S_t \) at time \( t \), in which there are three sources of uncertainty: a standard Brownian motion \( W_t \), an independent Poisson process of jump events \( N_t \) with intensity \( \lambda \), and a random jump size \( Z_t \) which is distributed lognormally.

The estimation procedures for jump-diffusion processes are standard and can be found, for example, in Rama and Tankov (2003) and Rüschendorf and Woerner (2002). Furthermore, Ait-Sahalia (2004) validated that such maximum likelihood methods can perfectly identify the diffusive and jump components, particularly in the context of the framework we follow here, Merton (1976).
with mean $\alpha$ and variance $\gamma^2$. The stock return dynamics are described by the following stochastic differential equation:

$$\frac{dS_t}{S_t} = (\mu - \lambda \cdot \kappa) \, dt + \sigma \cdot dW_t + dJ_t$$  \hspace{1cm} (1)

where $\mu$ and $\sigma$ are constants, $\kappa \equiv E(Z_t - 1)$ is the expected relative jump of $S_t$, and $J_t \equiv (Z_t - 1) \cdot N_t$ denotes the compound Poisson process.\textsuperscript{7} Following Merton (1976) and Navas (2003), the diffusive and jump components of total return variance can be expressed in terms of the respective process parameters as,

$$V^d = \sigma^2 t$$  \hspace{1cm} (2)

$$V^j = \lambda(\alpha^2 + \gamma^2) t$$

which allow for easily calculating the values of the variance components. The total return variance is just the summation of these two components,

$$V = V^d + V^j.$$  \hspace{1cm} (3)

Applying ML methodologies, we calibrate the model on historical data for stock returns and obtain a vector of parameter estimates $\theta_i = (\mu_i, \sigma_i, \lambda_i, \alpha_i, \gamma_i)$ for each stock $i$ estimated over period $t$. Based on $\theta_i$, we then calculate $V_{i,t}^d$ and $V_{i,t}^j$, that is, the respective components of the diffusive and jump variance components out of total variance.\textsuperscript{8} For a more detailed description of our framework, estimation procedure and their references see Appendix B.

### 2.2 Empirical Analysis

We estimate Fama-MacBeth regressions to formally test for different influences each type of variance has on liquidity. We first confirm that indeed total volatility has a positive effect on bid-ask spreads in our sample, as previous studies have shown. Therefore we run the...

\textsuperscript{7} We follow vast prior literature and do not model volatility as a stochastic process as some studies do. Although stochastic volatility makes the model more “realistic” it adds unnecessary complexity at the expense of tractability in the context of the current study. Moreover, simulation analysis reveals that the correlation between our estimated jump and diffusion parameters in a model with stochastic volatility to a model without stochastic volatility is 0.9 and therefore suggests that there is very little benefit for the additional complexity.

\textsuperscript{8} An alternative valid way to estimate jump parameters is to use option prices (e.g., Yan, 2011; Cremers, Halling and Weinbaum, 2015). However, many stocks do not have available options for trade. Moreover, trading and quotes are very "thin" and illiquid for other stock options. Therefore, to gain a better coverage of the market, and particularly to study liquidity and liquidity risk implications, we chose our methodology.
following cross-section regression year-by-year

\[ Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t} + \sum_{j=1}^{J} \beta_{1+j} Control_{i,t}^j + \varepsilon_{i,t} \quad (4) \]

where the dependent variable \( Liq_{i,t+1} \) denotes the relative bid-ask spread (in percent) for stock \( i \) in the following year \( t + 1 \). The explanatory variables on the right-hand side include total variance \( V_{i,t} \), \( J \) control variables \( Control_{i,t}^j \) for \( j = 1, \ldots, J \), and an error term \( \varepsilon_{i,t} \), all measured for stock \( i \) in year \( t \) (January 1 to December 31). This cross-section regression is estimated year-by-year, and then time-series averages are calculated for all coefficients, following the Fama-MacBeth method. Therefore this procedure yields a vector of estimates \( \beta = (\beta_0, \ldots, \beta_{1+J}) \) that characterizes the variables’ effect on liquidity.\(^9\)

Control variables include the log of market-capitalization and average turnover rate for stock \( i \) in year \( t \). Stoll (1978a, b), Jameson and Wilhelm (1992), and others have shown that bid-ask spreads depend on expected holding duration, as more trading decreases the duration of risk exposure. Therefore we expect to find a negative relation between turnover and illiquidity. As we discussed above, volatility and turnover exhibit a positive relation. Therefore we estimate this regression twice, once including turnover and once without, to gauge the indirect impact total volatility has on illiquidity through turnover.

In the next step, we explicitly include in the model the decomposition of total variance into its jump and diffusion-driven components. Therefore the new specification is

\[ Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t}^d + \beta_2 V_{i,t}^j + \sum_{j=1}^{J} \beta_{2+j} Control_{i,t}^j + \varepsilon_{i,t} \quad (5) \]

where the explanatory variables \( V_{i,t}^d \) and \( V_{i,t}^j \), the diffusion- and jump-driven variance components, respectively, replace the total variance \( V_{i,t} \) in Equation (4). Both \( V_{i,t}^d \) and \( V_{i,t}^j \) are obtained from the ML estimation. All other variables in the new specification remain unchanged. Again, we estimate this regression twice, once including turnover and once without, to gauge the indirect impact each volatility component has on illiquidity through turnover.

\(^9\)In our specification we test for lagged effects since for any decision made in year \( t + 1 \) the only information available is from year \( t \). However, in unreported results we repeated all our regressions using contemporaneous variables instead of lagged ones and find the same effects.

\(^{10}\)The fact that market-makers face high-frequency intra-day inventory risk should not be confused with our use of annual variables. These variables represent firm characteristics that represent jump and diffusive risks, not realized jumps or price changes. They represent the likelihood of jumps and diffusive price changes upon which market-makers base their approach to setting bid-ask spreads. As mentioned earlier, these characteristics are indeed estimated using higher frequency data (daily).
3 Data

We obtain from CRSP daily stock prices, volume, shares outstanding, and market-capitalization for all stocks listed on the NYSE and NASDAQ between 2002–2011. We start our sample in 2002, as this is the last year of the minimum tick rules, which imposed regulatory constraints on minimum bid-ask spreads and price changes. For these stocks and years, we also obtain TAQ historical data for bid-ask quotes and calculate their average annual percentage spreads. We calculate average annual turnover rates using volume and shares outstanding data for each stock.

In our final sample, we eliminate all firm-years with less than 245 observations per year, and those with bid-ask spreads (percent) that were larger than 50% or negative. We also eliminate securities that did not have data on market capitalization for year $t$ in the CRSP database; this excludes non-stock securities listed on exchanges. We end up with 9,088 different stocks between 2002–2011, and 61,299 stock-year observations.

We calibrate the return-process model specified in Equation (1) for daily returns and obtain for each stock $i$ and year $t$ a vector of parameters $\theta_i^t = (\mu_i^t, \sigma_i^t, \lambda_i^t, \alpha_i^t, \gamma_i^t)$ that characterizes the jump-diffusion return process. To gauge the consistency of our calibration with the realized historical data, we compare our model-implied daily-return variance ($\tilde{V}_t^i$ as specified in Equation (3)) with the realized daily return-variance, measured over the corresponding year $t$. We denote the realized variance by $V_t^i$. For more than 90% of our sample, the ratio $\tilde{V}_t^i / V_t^i$ falls between 0.8 and 1.2, implying that there was a good fit between our predicted variance and the actual variance, i.e., no more than 20% deviation.

Finalizing our sample, we eliminate all estimates with extreme values, that is, the highest and lowest 1% for all parameters of the vector $\theta_i^t$. We also eliminate all observations that do not satisfy the condition $\tilde{V}_t^i / V_t^i \in [0.8, 1.2]$. After applying these additional filters, our final sample contains 44,171 stock-years observations. The average jump size $\alpha$ in our sample is 3% (in absolute values), and the average jump frequency $\lambda$ is 16%. These estimates are comparable to estimates obtained by prior studies (e.g., Todorov and Bollerslev, 2010; Tauchen and Zhou, 2011).

4 Descriptive Statistics

Panel A of Table (1) reports overall average and quintile values for total volatility, jump volatility, and diffusive volatility. Average total return volatility across all years and stocks

\[^{11}\]This final elimination does not alter the inferences reported in this paper.
is around 29%. Average values for the diffusive and jump components are of the same order of magnitude, 18% and 20%, respectively, and their medians are around 17%.

Panel B reports quintile breakdown of average bid-ask spreads across our sample. They are around 1.8% on average with a standard deviation of 2.5%. The median bid-ask spread is around 85 basis points.

5 Results

5.1 Univariate Analysis - Sorted Portfolios

As a first step we provide a univariate analysis in a portfolio framework. We explore the impact each volatility component has on illiquidity while controlling for the levels of the other volatility component. In Table (2) Panel A, we sort all stocks in our sample for each year $t$ on their jump-driven variance portion $V^j$ and form five equally weighted portfolios. The first quintile portfolio contains stocks with the lowest jump volatility component for a given year, and the fifth quintile contains stocks with the highest jump volatility component. We denote these portfolios by $j = 1, ..., 5$. Then, for each year $t$, we further sort each of the five portfolios $j = 1, ..., 5$ on their diffusion-driven variance component $V^d$ to form additional five equally weighted subportfolios per portfolio rank $j$. The first quintile subportfolio contains stocks with the lowest $V^d$ and the fifth quintile subportfolio contains stocks with the highest $V^d$. This way, we create for each year $t$ and jump portfolio rank $j$ five subgroups of stocks ranked from 1-5 sorted on $V^d$. We denote these subportfolios by $d_j = 1, ..., 5$. We then calculate average bid-ask spreads for each subportfolio in year $t + 1$.

As seen in Panel A, going up the ranking in the diffusive volatility component while holding jumps levels fixed has a (small) negative effect on bid-ask spreads. Overall the difference in average bid-ask spreads between high diffusive and low diffusive volatility portfolios are all negative and around $-65$ basis points, with high $t$-statistics ranging from $-7.76$ to $-13.10$. The only exception is for the highest jump portfolio that exhibits a very small and insignificant difference in bid-ask spreads between its high and low diffusive volatility portfolios. We provide a graphic presentation of these results in Figure 1 Panel A.

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12 The jump and diffusive volatility components do not sum up to total volatility for two reasons. First, the equality holds true for variances and not for standard deviations. Additionally, for total standard variations of returns we use realized standard deviations, while for the diffusive and jump components, we use model implied volatilities. These values are close but not identical.
In Panel B of Table (2) we repeat the same procedure the other way around. That is, we sort all stocks on the diffusive variance component \( V^d \) and then further sort each diffusive portfolio \( d = 1, ..., 5 \) on the jump variance component. This way, we create for each year \( t \) and diffusive portfolio rank \( d \) five subportfolios ranked from 1–5 sorted on \( V^j \). We denote these subportfolios by \( j_d = 1, ..., 5 \). We then calculate the average bid-ask spread for each portfolio (in year \( t + 1 \)).

A very different picture arises for this analysis. As seen in Panel B, bid-ask spreads increase when going up the ranking in the jump volatility component while controlling for diffusive volatility levels. This holds true for all levels of diffusive volatility. The difference in means for bid-ask spreads between high- and low-jump volatility portfolios are all positive and range from 164 to 278 basis point, much larger than for those obtained for the diffusive case in absolute terms reported Panel A. Moreover, \( t \)-statistics are much higher for the jump case and range from 18.94 to 27.57, indicating much higher statistical significance. We provide a graphic presentation of these results in Figure 1 Panel B.

### 5.2 Fama-MacBeth Regressions: Total Volatility and Illiquidity

In the first step, we replicate the results from previous studies to confirm that total volatility has a positive impact on illiquidity in our sample. Table (3) reports Fama-MacBeth regression results based on the model specified in Equation (4). We estimate Equation (4) twice, once without controlling for turnover and again controlling for turnover (Models 1 and 2, respectively). Total variance indeed has a positive and significant impact on bid-ask spreads under both specifications. Under the first specification, the coefficient estimate for total variance is 2.19 with a \( t \)-statistic of 5.52. Under the second specification, the coefficient estimate increases to 3.44 with a \( t \)-statistic of 6.02. The turnover coefficient is negative, as expected, consistent with prior studies that argue that higher trading activity decreases illiquidity. The coefficient for total volatility becomes more positive since here we explicitly account for the negative impact turnover has on illiquidity, capturing only the pure relation between total volatility and illiquidity and ignoring its indirect negative effect through turnover.\(^{13}\)

Market capitalization also has a negative and statistically significant effect as expected, since larger firms tend to have lower trading costs. These findings are consistent with prior studies that found a positive relation between volatility and illiquidity costs. (See Stoll, 1978b, 2000; Pastor and Stambaugh, 2003).

\(^{13}\)We confirmed that total volatility and turnover have a significant positive correlation. When we regressed \( \text{Turnover} \) on \( \text{Total Volatility} \) we received a positive coefficient of 161.5 for \( \text{Total Volatility} \) with \( t \)-statistic of 5.51.
5.3 Fama-MacBeth Regressions: Volatility Components and Illiquidity

In the next step, we decompose total volatility into its jump and diffusive driven components. Table (4) reports Fama-MacBeth regression results for the regression specified in Equation (5), which explicitly models separate effects for each component. Again, we estimate this equation twice, without controlling for turnover and then controlling for turnover (Models 1 and 2, respectively). The estimated effects of jump and diffusive volatilities are very different under both specifications. Under the first specification, the jump-driven variance coefficient is 4.25, and the diffusive one is −1.87, and both are statistically significant with t-statistics of 7.84 and −4.14, respectively. This implies that the two volatility components affect illiquidity very differently: the jump component positively and the diffusive negatively. These coefficients imply that an increase of one standard deviation in the jump-driven volatility component increases bid-ask spreads by approximately 30 basis points, whereas an equivalent increase in the diffusive volatility component decreases bid-ask spreads by approximately 10 basis points. However, the negative effect of diffusive volatility might be attributable to its indirect effect on illiquidity through increasing turnover, as discussed before.14

To explicitly account for turnover effects, we use Model 2. Under this specification the jump-driven variance coefficient increases to 5.15, while the diffusion-driven variance coefficient dramatically drops to 0.02. Moreover, the jump-component coefficient has a substantially higher statistical significance, with a t-statistic of 8.30 compared to 0.04 for the diffusion component. These coefficients imply that an increase of one standard deviation in the jump-driven volatility component increases bid-ask spreads by approximately 40 basis points, whereas an equivalent increase in the diffusive volatility component has negligible economic effects. The turnover coefficient is negative, similar to that obtained for total volatility in Table (3). This implies that the entire relation between diffusive volatility and illiquidity is indirect, and it is completely driven by turnover. In contrast, the relation between jump volatility and illiquidity is direct and unrelated to increased trading activity. Finally, firm size maintains a very similar effect compared to those obtained in Table (3) and Table (4) Model 1. The Fama-MacBeth average $R^2$ is 50%, indicating a strong explanatory power for our model.

14We confirmed that turnover has a different correlation with each volatility component. When we regressed Turnover on Jump Volatility and Diffusive Volatility we received a (small) negative coefficient of -78.8 for Jump Volatility with t-statistic of -1.71. On the other hand, for Diffusive Volatility we received a large positive coefficient of 787.9 with t-statistic of 8.12. These results are consistent with those previously obtained in the literature (e.g., Giot et al., 2010).
In summary, our results indicate that the structure of volatility matters for bid-ask spreads beyond raw levels of volatility. Moreover, the jump-driven volatility component almost exclusively drives the relation between volatility and illiquidity, while the diffusive component has a negligible effect. The only effect diffusive volatility has is indirect and driven by the increased trading it generates.

An alternative yet equivalent way to state our results is that controlling for total volatility, the jump volatility component has a strong positive effect on illiquidity whereas the diffusive component has a negative effect. Although this analysis is exactly equivalent to the one carried out thus far using Model 2, for convenience and ease of presentation reasons, we report estimation results for the effects jump and diffusive volatility have on illiquidity when controlling for total volatility. These results are presented in the last two columns of Table (3), using Model 2a and 2b respectively. The coefficient estimates in Model 2a and 2b match their implied values from the coefficient estimates in Model 2.\(^{15}\)

### 5.4 Controlling for Information Asymmetry

In the previous sections we showed that the association between volatility and liquidity is driven almost exclusively by the jump component. Alternatively stated, our results show that the jump source of volatility is associated with liquidity, controlling for total volatility. As discussed in the introduction, because the structure of volatility is governed by the information environment of the firm, this result provides a link between the information environment and liquidity. Nevertheless, prior literature has already established a link between the information environment of the firm and liquidity through information asymmetry. Our predictions suggest that the information environment is likely to create observable differences in liquidity even for firms with identical information asymmetry (or even in the absence of information asymmetry).

We test this predication in two different ways. In the first way, we simply add a control variable to Equation (5) to account for levels information asymmetry. In the second way, we sort our sample into five quintiles of information asymmetry and re-estimate Equation (5) in each quintile. Our empirical proxy for information asymmetry is the probability of informed trade (PIN). PIN is based on the imbalance between buy and sell orders among investors and is therefore technically unrelated to bid-ask spread. The PIN measures are obtained from Stephen Brown’s website and are based on Brown and Hillegeist (2007). In

\(^{15}\)To see this clearly, define the bid-ask spread as \(y\), jump volatility as \(x_1\), diffusive volatility as \(x_2\), and total volatility as \(x_3\), where \(x_3 = x_1 + x_2\). If \(y = \alpha x_1 + \beta x_2\) then \(y = (\alpha - \beta)x_1 + \beta x_3\) and \(y = (\beta - \alpha)x_2 + \alpha x_3\).
their paper they compute PINs using the Venter and De Jong (2006) model to extend the Easley et al. (1997) model.

The results from these tests are presented in Table (5). The first column presents estimation results for Equation (5) when controlling for information asymmetry. The results reveal that although PIN is, as expected, positively associated with bid-ask spreads, all our other results remain qualitatively unchanged (as in Table 4). Columns 2-6 present estimation results for Equation (5) for each information asymmetry quintile from low to high separately. The coefficient for jump volatility is positive with high \( t \)-statistics in all quintiles, while the coefficient for diffusive volatility is mostly negative and has very low \( t \)-statistics. Taken together, these results suggest that the relation between each source of volatility and liquidity remains unaltered even for firms with similar levels of information asymmetry.\(^{16}\)

5.5 Robustness - Testing for Reverse Causality

By definition, illiquid assets are subject to greater jump risk as thin trading means infrequent transactions where each transaction is more likely to generate large price impacts. Put differently, “technical jumps” can be generated through prices that bounce between bid and ask quotes for wide bid-ask spreads.

To mitigate the concern that this reverse causality drives our results, we test for the effect of increasing the jump volatility component while controlling for turnover rates. By construction, stocks with high turnover rates do not exhibit thin trading. Therefore, we first sort all stocks in each year on turnover rates and form five different portfolios, from low to high. Then, for each portfolio level, we repeat our second method of double sorting on total variance and jump-driven variance and then averaging across all years and all total volatility ranks \( k \). This process is carried out for each of the five turnover portfolios. Therefore we have a five-by-five portfolio ranking sorted on turnover level and jump-driven volatility level. We report the results in Table (6).

Our results show that the dominance of the jump volatility component is maintained in all portfolios: higher jump-driven portfolios always exhibit higher average bid-ask spreads, for all five turnover portfolios. Formal \( t \)-tests for the difference between high and low jump-portfolios all reject the null hypothesis that the corresponding average bid-ask spreads are

\(^{16}\)These tests do not suggest that the structure of volatility does not affect liquidity through information asymmetry as well. Nor do these tests suggest that the information environment does not affect liquidity through information asymmetry. These result simply suggest that the information environment can affect liquidity through its effect on volatility structure independently of the effects the information environment has on liquidity through information asymmetry.
identical per turnover portfolio, with \( t \)-statistics ranging from 8.26–10.76. This suggests that jump volatility plays an important role even for stocks that do not suffer from thin trading.

6 Volatility Components and Liquidity Risk

A number of studies have shown that liquidity levels are risky (e.g., Pastor and Stambaugh, 2003; Sadka, 2006).\(^{17}\) Given our findings about the differential effects jump and diffusive volatilities have on liquidity, to the extent that some of this relation is driven by systematic factors, it is possible that these components would play different roles in determining liquidity risk.

Acharya and Pedersen (2005) use a liquidity-adjusted CAPM model to provide a unified framework that accounts for the various effects liquidity risk has on asset prices. In their model, the CAPM “beta” is decomposed into the standard market beta and additional three liquidity-related betas, representing three different channels through which liquidity risk operates: (1) the sensitivity of the stock’s illiquidity to the market’s illiquidity; (2) the sensitivity of the stock’s return to the market’s illiquidity; and (3) the sensitivity of the stock’s illiquidity to the market’s return. Investors demand higher risk premiums for stocks that suffer more in times of stress, times in which they also exhibit large losses in wealth. That is, investors should worry about a security’s performance and tradability both in market downturns and when liquidity “dries up”.

While Acharya and Pedersen’s (2005) model gives clear predictions as to the effects these three sensitivities have on stocks’ expected returns, they recognize that they do not explain why different stocks possess those different sensitivity characteristics. Rather, they merely estimate the sensitivities and treat them as given. Our framework allows for a deeper insight into the heterogeneity of these characteristics, which complements their analysis.

The relation between jump volatility and two of the liquidity risk channels described above is straightforward. The first and third channels describe the comovement in individual stock illiquidity with market illiquidity and market returns, respectively, over time. Since we showed that the jump-volatility component is the dominant driver behind illiquidity, it is possible that it would also be the main driver determining its commonality with the other two variables.

The second channel, which describes the comovement between returns and market liquidity, might also be driven by jump risk. Firms with higher jump risk are more likely to experience

\(^{17}\) Amihud and Mendelson (2015) review this literature, see additional references therein.
large losses (i.e., a negative jump) when markets "dry up" for lack of funding, thus increasing the commonality between returns and market liquidity. Furthermore, trading costs for individual stocks might also increase in an illiquid environment and thus put downward pressure on prices. Since liquidity costs are driven by jump risk, it is possible that these firms with higher jump risk that are more likely to experience price declines in illiquid markets.

To test these possibilities we follow Acharya and Pedersen (2005) and construct equivalent measures for the three liquidity-related betas. If indeed jump-risk is the dominant driver behind illiquidity, it is possible that higher values for all three liquidity-related betas are correlated with higher measures for jump-risk. In contrast, diffusive-risk should be less correlated with these betas.

Specifically, let $\beta^{1L}, \beta^{2L}$ and $\beta^{3L}$ denote the three liquidity related betas, respectively. Following Acharya and Pedersen (2005), we define

$$
\beta_{i,t}^{1L} = \text{cov} \left( L_i^t, L_M^t \right) \quad \beta_{i,t}^{2L} = \text{cov} \left( r_i^t, L_M^t \right) \quad \beta_{i,t}^{3L} = \text{cov} \left( L_i^t, r_M^t \right)
$$

where $L_i^t$ and $L_M^t$ are liquidity measures for stock $i$ and for the aggregate market $M$. Similarly, $r_i^t$ and $r_M^t$ are stock $i$ returns and market returns, respectively.

To estimate these $\beta$’s we used the Sadka (2006) variable-permanent liquidity factor as our measure for aggregate market liquidity, which is the one associated with information driven price changes. For individual stock liquidity measures we used the (negative) value of monthly average TAQ bid-ask spreads per stock.\footnote{We used their negative value to convert them from measures of illiquidity (costs) to measure of liquidity, to be consistent with the Sadka (2006) framework and liquidity factors.} All monthly return data and aggregate market return data were obtained from CRSP. As in Acharya and Pedersen (2005) we expect all three betas to be positive, that is, the higher the beta the larger liquidity risk is.

For each month between 2002-2011 we used a 60-month rolling window to estimate the three covariances (betas) per stock $i$ as in Equations (6).\footnote{In practice, instead of using simple covariances we used OLS regressions to estimate these three $\beta$’s, where each $\beta$ was obtained as the estimated coefficient.} Then, for each beta we ran a Fama-MacBeth regression on our two measures of jump and diffusive volatility, $V_{i,t}^d$ and $V_{i,t}^j$. That is,

$$
\beta^k_{i,t} = \alpha + \gamma_1 V_{i,t}^d + \gamma_2 V_{i,t}^j + \gamma_3 \ln(size_{i,t}) + \varepsilon_{i,t}
$$

where, $k$ is $1L, 2L$ or $3L$. We also included (the log of) the firm’s market capitalization as a control variable. We report our results in Table (7).
As seen in Table (7), the jump volatility component has a positive and statistically significant effect for all three betas. On the other hand, the diffusive component has a (non-significant) negative effect. That is, only jump volatility increases liquidity risk while diffusive volatility does not.

Furthermore, to enhance our analysis, we followed Pastor and Stambaugh (2003) to take a deeper look into the factors determining $\beta_{i,t}^{2L}$, which measures the relation between returns and market liquidity. They first obtained $\beta_{i,t}^{2L}$ using a richer specification based on a three-factor Fama-French (FF) model. Specifically,

$$r_{i,t} = \beta_{i}^{0} + \beta_{i}^{M} MKT_t + \beta_{i}^{S} SMB_t + \beta_{i}^{H} HML + \beta_{i}^{2L} L_{t}^{M} + \varepsilon_{i,t}$$

(8)

where $MKT_t$, $SMB_t$, and $HML_t$ are the regular FF factors (market, small minus big, and high minus low, respectively) and $L_{t}^{M}$ is the aggregate liquidity factor. Therefore, $\beta_{i,t}^{2L}$ is the coefficient for the aggregate liquidity factor. They also assumed that $\beta_{i,t}^{2L}$ has the following linear form,

$$\beta_{i,t}^{2L} = \psi_{1,i} + \psi'_{2,i} Z_{i,t-1}$$

(9)

where $Z_{i,t-1}$ is a vector of characteristic variables that affect $\beta_{i,t}^{2L}$. Therefore, Equation (8) can be rephrased as,

$$r_{i,t} = \beta_{i}^{0} + \beta_{i}^{M} MKT_t + \beta_{i}^{S} SMB_t + \beta_{i}^{H} HML + (\psi_{1,i} + \psi'_{2,i} Z_{i,t-1}) L_{t}^{M} + \varepsilon_{i,t},$$

from which we can define the following residual,

$$e_{i,t} = r_{i,t} - \beta_{i}^{M} MKT_t - \beta_{i}^{S} SMB_t - \beta_{i}^{H} HML$$

that can be expressed as,

$$e_{i,t} = \psi_{0} + \psi_{1,i} L_{t}^{M} + \psi'_{2,i} Z_{i,t-1} L_{t}^{M} + v_{i,t}.$$  

(10)

Namely, $e_{i,t}$ is the share of returns that remains unexplained by all regular factors and is affected only by liquidity.

Estimating $\psi_{2,i}$ allows for gauging the contribution each characteristic in $Z$ has on liquidity risk, $\beta_{i,t}^{2L}$, as defined in Equation (9). In the context of our analysis, we used jump volatility and diffusive volatility as two characteristics in $Z$ and our goal is to measure how each characteristic affects $\beta_{i,t}^{2L}$.

We report our regression results for Equation (10) in Table (8), where estimates for $\psi_{1}$ and $\psi'_{2}$ are reported separately. Focusing on the vector of coefficients $\psi'_{2}$ it can be seen that
jump and diffusive volatilities have very different effects. The interactions between the jump component and both Sadka (2006) liquidity factors have positive and statistically significant coefficients. On the other hand, the interactions between the diffusive component and the liquidity factors are non-significant. That is, this richer framework for the liquidity measure also supports the unique role jump volatility plays: given the structure of $\beta_{i,t}^{2L}$ specified in Equation (9), only the jump volatility component increases liquidity risk.

In summary, these findings provide further support for the dominant role jump volatility plays in the relation between volatility and liquidity. Not only liquidity levels are driven by the jump component but liquidity risk as well. We do not find a similar significant effect for the diffusive component. Finally, this pattern exists in all three channels through which liquidity risk operates.

7 Conclusions

In our analysis, we delve a deeper look into the different factors determining the relation between total volatility and illiquidity. Disentangling total volatility into its diffusive and jump components reveals a more complex picture. We find that it is jump volatility that drives the positive relationship, while diffusive volatility has a negative contribution. These results are maintained at any level of information asymmetry. Moreover, the negative contribution of diffusive volatility is completely channeled through its effect on increased trading activity (turnover), which in return decreases illiquidity. Therefore, once we account for this trading effect the diffusive component plays no role.

Finally, we also find that the differential effects each volatility component has on illiquidity carry on in the same structural fashion into additional dimensions of illiquidity. That is, each volatility component maintains its type of impact on liquidity risk and liquidity risk premiums.

These findings contribute to several different strands of the academic literature. They further expand our understanding of the determinants of liquidity, particularly in relation to the role volatility plays, and of the way firms’ information environment affects capital markets. Moreover, they enhance our understanding of the mechanisms that drive liquidity risk and liquidity risk premiums. Finally, they shed light on a set of new consequences that jumps create, in addition to a number of previously documented ones, such as their consequences to credit risk, market beta, and stock option pricing.

At the regulatory level, our study provides evidence that implementing accounting policies
that encourage more continuous flow of information and disclosure may make sense in order to increase liquidity. Such policies are likely to improve the diffusive component of volatility, smooth potential surprises, and thus improve liquidity.

Last, we realize that we do not offer an explicit theoretical model to gauge the different effects that jump and diffusive volatilities have on liquidity. Nevertheless, the theoretical paradigms mentioned in the introduction provide the inspiration for our empirical investigation, which is significant in itself, particularly given the fact that so far no work has been done on the topic. Therefore, our findings provide the motivation for further developments of an explicit theoretical model, which is left for future research.
Appendix A: Jumps and the Information Environment

In this appendix we replicate in our sample period (2002-2011) the results obtained in our companion study. Panel A of the following table presents regression results for jump volatility on various proxies for information environment and time and firm fixed effects. The number of analysts covering the firm, the fact that management provides guidance, and the number of management guidance by the firm, are all negatively associated with the jump component of total volatility (coefficients of -0.042, -0.178 and -0.023 respectively). The results in Panel B, using a difference in differences with time and firm fixed effects design, show that a drop in analyst coverage as a result brokerage house closure casually increases jump volatility in the year of the change compared to unaffected years and firms (coefficient of 0.039). Taken together and as suggested by our companion study, these results provide confirmation that the information environment determines the composition of volatility.

<table>
<thead>
<tr>
<th>Information proxy</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>Firm &amp; Year fixed effects</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of analysts</td>
<td>-0.042</td>
<td>-20.23</td>
<td>Yes</td>
<td>55,558</td>
</tr>
<tr>
<td>Management forecast (Yes/No)</td>
<td>-0.178</td>
<td>-9.50</td>
<td>Yes</td>
<td>55,558</td>
</tr>
<tr>
<td>Number of management forecasts</td>
<td>-0.023</td>
<td>-8.98</td>
<td>Yes</td>
<td>55,558</td>
</tr>
<tr>
<td>Panel B</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drop in analyst coverage due to closure of brokerage house</td>
<td>0.039</td>
<td>3.93</td>
<td>Yes</td>
<td>55,558</td>
</tr>
</tbody>
</table>
Appendix B: Model and Estimation Method

Following Merton (1976), let \( S_t \) denote a stock price at time \( t \) on a filtered probability space \((\Omega, \mathcal{F}, (\mathcal{F}_t), P)\), which is assumed to satisfy the following stochastic differential equation:

\[
\frac{dS_t}{S_t} = (\mu - \lambda \cdot E(Z - 1)) dt + \sigma dW_t + (Z - 1) dN_t,
\]

where \( \mu \) and \( \sigma^2 \) denote the instantaneous mean and variance of the stock return in the absence of jumps, and \( W_t \) is a Wiener process. Furthermore, \( N_t \) is a Poisson process with intensity \( \lambda > 0 \), and \( Z \) is the log-normal jump amplitude with \( \ln Z \sim N(\alpha; \gamma^2) \) such that

\[
E(Z - 1) = \exp(\alpha + \frac{\gamma^2}{2}) - 1.
\]

We postulate that \( W_t, N_t, \) and \( Z_t \) are mutually independent. The parameter vector \( \theta \) is

\[
\theta = (\mu, \sigma^2, \lambda, \alpha, \gamma^2)',
\]

where \( \alpha \) and \( \gamma^2 \) represent the mean and variance of the jump size of stock returns.

Since the Brownian motion and the Poisson process of jump events are independent, the total return variance can be decomposed into

\[
V \equiv Var\left(\frac{S_t}{S_0}\right) = Var(\sigma W_t) + Var(J_t), \tag{11}
\]

which is the sum of the diffusion-related variance and the jump-related variance. We denote

\[
V^d \equiv Var(\sigma W_t), \quad V^j \equiv Var(J_t)
\]

as the respective variances. Furthermore, following Merton (1976) and Navas (2003), these variances can be expressed in terms of the respective basic process parameters as

\[
V^d = \sigma^2 t \quad V^j = \lambda (\alpha^2 + \gamma^2) t, \tag{12}
\]

which allow for easily calculating these values based on the parameter vector \( \theta \).

Following Ait-Sahalia (2004), under the assumptions specified above, the transition density \( f_{\Delta \ln S} \) of \( \ln S_t \) can be expressed by

\[
f_{\Delta \ln S}(x; \theta) = (1 - \lambda \cdot \Delta t) \cdot f_{\Delta \ln S|\Delta N_t=0}(x|\Delta N_t = 0; \theta) + \lambda \cdot \Delta t \cdot f_{\Delta \ln S|\Delta N_t=1}(x|\Delta N_t = 1; \theta),
\]

where

\[
f_{\Delta \ln S|\Delta N_t=0}(x|\Delta N_t = 0; \theta) = \frac{1}{\sqrt{2\pi \Delta}} \exp\left(-\frac{(x - \mu)^2}{2\Delta}\right)
\]

and

\[
f_{\Delta \ln S|\Delta N_t=1}(x|\Delta N_t = 1; \theta) = \frac{1}{\sqrt{2\pi \Delta}} \exp\left(-\frac{(x - \mu - \Delta \cdot \ln Z)^2}{2\Delta}\right)
\]

with

\[
\Delta = \sqrt{2\sigma^2 \Delta t}, \quad \mu = \mu - \lambda \cdot \Delta t, \quad \lambda = \lambda \cdot \Delta t, \quad \Delta \cdot \ln Z = \Delta \cdot \alpha + \frac{\Delta \cdot \gamma^2}{2}.
\]
where \( f_{\Delta \ln S|\Delta N_t=0} \) and \( f_{\Delta \ln S|\Delta N_t=1} \) represent the transition densities of \( \ln S_t \), conditioning on \( \Delta N_t = 0 \) and \( \Delta N_t = 1 \) jumps between two sampling points, respectively, and \( \Delta t > 0 \) denotes the time distance between sampling points. Since

\[
\begin{align*}
P(\Delta N_t = 0) &= 1 - \lambda \cdot \Delta t + o(\Delta t) \\
P(\Delta N_t = 1) &= \lambda \cdot \Delta t + o(\Delta t) \\
P(\Delta N_t > 0) &= o(\Delta t),
\end{align*}
\]

additional jumps between two sampling points are neglected. Closed form expressions for the conditional densities are given by

\[
f_{\Delta \ln S|\Delta N_t=k}(x|\Delta N_t=k; \theta) = \frac{1}{\sqrt{2 \cdot \pi \cdot v(k)}} \cdot \exp \left( - \frac{(x - m(k))^2}{2 \cdot v(k)} \right),
\]

where

\[
\begin{align*}
m(k) &= (\mu - \sigma^2/2 - \lambda \cdot E(Z - 1)) \cdot \Delta t + k \cdot a \\
v(k) &= \sigma^2 \cdot \Delta t + k \cdot \gamma^2,
\end{align*}
\]

with \( k \in \{0, 1\} \). Based on a sample of \( n \) stock returns \( \Delta \ln s_1, \ldots, \Delta \ln s_n \), the resulting likelihood estimate \( \hat{\theta} \) of \( \theta \) is computed numerically as

\[
\hat{\theta} = \arg \max_{\theta} \left( \sum_{i=1}^{n} \ln f_{\Delta \ln S}(\Delta \ln s_i; \theta) \right).
\]
Appendix C: Variable Description

1. $\mu$ - Constant parameter of the diffusion process representing the diffusive drift.

2. $\sigma$ - Constant parameter of the diffusion process representing the diffusive volatility.

3. $\lambda$ - Constant parameter of the compound jump process representing the average number of jumps per annum (year).

4. $\alpha$ - Constant parameter of the compound jump process representing the average jump size.

5. $\gamma$ - Constant parameter of the compound jump process representing the standard deviation of the jump size $\alpha$.

6. **Bid-Ask Spread** ($Liq_{i,t}$) - Annual average bid-ask spread for firm $i$ across all intraday quotes based on available TAQ data.

7. **Total Var** - Annual total return variance for stock $i$ in year $t$, $V_{i,t}$; see Equation (7).

8. **Diffusive Var** - The diffusive component of annual total return variance for stock $i$ in year $t$, $V_{i,t}^{d}$; see Equation (8).

9. **Jump Var** - The jump component of annual total return variance for stock $i$ in year $t$, $V_{i,t}^{j}$; see Equation (8).

10. **Turnover** - The average ratio of daily volume to shares-outstanding for firm $i$ in year $t$.

11. $ln(size)$ - The natural log of firm $i$’s market capitalization in year $t$. 

References


Figure 1

BID-ASK SPREADS AND VOLATILITY COMPONENTS: SORTED PORTFOLIOS

This figure is a graphic presentation of Table (2). Panels A and B plot average bid-ask spreads per volatility level. Each graph in panel A controls for a jump volatility level, and each graph in Panel B controls for a diffusive volatility level.

Panel A: Diffusive Volatility Levels

Panel B: Jump Volatility Levels
Table 1: **DESCRIPTIVE STATISTICS.** This table reports descriptive statistics for our basic variables. Panel A reports average estimates for total, jump, and diffusive daily standard deviations as defined in Equations (2) and (3). Panel B reports average annual bid-ask spreads. Averages are calculated across all years and stocks in our sample. For total standard deviations of returns, we used realized standard deviations, while for the diffusive and jump components we used model implied volatilities. The number of observations in our sample is 55,558. See Appendix B for variable description.

<table>
<thead>
<tr>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>25</th>
<th>Mdn</th>
<th>.75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Daily Return Volatility (Std)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
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<td>.0168</td>
<td>.0050</td>
<td>.0169</td>
<td>.0255</td>
<td>.0376</td>
</tr>
<tr>
<td>Diffusion</td>
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<td>.0100</td>
<td>0</td>
<td>.0111</td>
<td>.0170</td>
<td>.0243</td>
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<tr>
<td>Jump</td>
<td>.0203</td>
<td>.0159</td>
<td>0</td>
<td>.0090</td>
<td>.0173</td>
<td>.0286</td>
</tr>
<tr>
<td><strong>Panel B: Liquidity Costs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bid-Ask Spread</td>
<td>.0187</td>
<td>.0252</td>
<td>.0003</td>
<td>.0030</td>
<td>.0085</td>
<td>.0235</td>
</tr>
</tbody>
</table>

28
Table 2: **UNIVARIATE ANALYSIS: SORTED PORTFOLIOS.** We sorted all stocks per year on one volatility component and then sorted again on the other component. In Panel A, we first sorted on jump volatility and formed $j = 1, ..., 5$ portfolios. Then, each jump portfolio $j$ was sorted again on diffusive volatility, to form additional five portfolios. This allows for testing the marginal effect of increasing total volatility by increasing the diffusive volatility alone, while controlling for the jump component. In Panel B, we first sorted on the diffusive volatility and then on jump volatility to test the marginal effect of jump volatility while controlling for diffusive volatility. Averages in each portfolio represent average bid-ask spreads in period $t + 1$. We also report the differences in bid-ask spreads between the highest and lowest portfolios and their $t$-statistics.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Low</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Controlling for Jumps</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Diffusive</td>
<td>.0166</td>
<td>.0169</td>
<td>.0204</td>
<td>.0253</td>
<td>.0364</td>
</tr>
<tr>
<td>2</td>
<td>.0141</td>
<td>.0106</td>
<td>.0133</td>
<td>.0190</td>
<td>.0270</td>
</tr>
<tr>
<td>3</td>
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<td>.0088</td>
<td>.0113</td>
<td>.0166</td>
<td>.0262</td>
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<tr>
<td>4</td>
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<td>.0089</td>
<td>.0102</td>
<td>.0139</td>
<td>.0294</td>
</tr>
<tr>
<td>High Diffusive</td>
<td>.0093</td>
<td>.0102</td>
<td>.0139</td>
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<td>.0361</td>
</tr>
<tr>
<td>High-Low</td>
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<td>-.0067</td>
<td>-.0065</td>
<td>-.0068</td>
<td>-.0003</td>
</tr>
<tr>
<td>$t$-stat</td>
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<td>-10.95</td>
<td>-8.42</td>
<td>-7.76</td>
<td>-0.20</td>
</tr>
<tr>
<td><strong>Panel B: Controlling for Diffusion</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Jump</td>
<td>.0162</td>
<td>.0085</td>
<td>.0097</td>
<td>.0090</td>
<td>.0115</td>
</tr>
<tr>
<td>2</td>
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<td>.0090</td>
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<td>.0160</td>
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<td>.0125</td>
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<tr>
<td>4</td>
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<td>.0169</td>
<td>.0284</td>
</tr>
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<td>.0261</td>
<td>.0285</td>
<td>.0393</td>
</tr>
<tr>
<td>High-Low</td>
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<td>.0164</td>
<td>.0194</td>
<td>.0278</td>
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<tr>
<td>$t$-stat</td>
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<td>22.90</td>
<td>20.86</td>
<td>24.80</td>
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</tbody>
</table>
Table 3: **FAMA MAC-BETH REGRESSION RESULTS: TOTAL VOLATILITY AND ILLIQUIDITY.** This table reports Fama-MacBeth regression results for the basic case of measuring the effect total volatility has on bid-ask spreads, as specified in Equation (4): $\text{Liq}_{i,t+1} = \beta_0 + \beta_1 V_{1,t} + \beta_2 \ln(\text{size}_{i,t}) + \beta_3 \text{turnover}_{i,t} + \epsilon_{i,t}$. This equation is estimated twice: not controlling and controlling for turnover (Models 1 and 2, respectively). $t$–statistics are reported in parentheses, and *** denotes one percent statistical significance. See Appendix B for variable description.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.1209***</td>
<td>0.1145***</td>
</tr>
<tr>
<td></td>
<td>(10.90)</td>
<td>(12.90)</td>
</tr>
<tr>
<td>Total Var</td>
<td>2.1974***</td>
<td>3.4452***</td>
</tr>
<tr>
<td></td>
<td>(5.52)</td>
<td>(6.02)</td>
</tr>
<tr>
<td>$\ln(\text{size})$</td>
<td>-0.0082***</td>
<td>-0.0076***</td>
</tr>
<tr>
<td></td>
<td>(-10.09)</td>
<td>(-11.93)</td>
</tr>
<tr>
<td>Turnover</td>
<td>-</td>
<td>-0.0015***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(-5.50)</td>
</tr>
<tr>
<td>Average-(R^2)</td>
<td>48%</td>
<td>50%</td>
</tr>
<tr>
<td>Observations</td>
<td>44,171</td>
<td>44,171</td>
</tr>
</tbody>
</table>
Table 4: **FAMA MAC-BETH REGRESSION RESULTS: MAIN RESULTS–VOLATILITY COMPONENTS AND ILLIQUIDITY.** This table reports Fama-MacBeth regression results for the marginal effects each volatility component has on bid-ask spreads, as specified in Equation (5): \( \text{Liq}_{i,t+1} = \beta_0 + \beta_1 V_{1,t}^d + \beta_2 V_{1,t}^j + \beta_3 \ln(size_{i,t}) + \beta_4 \text{turnover}_{i,t} + \epsilon_{i,t} \). This equation is estimated twice: not controlling and controlling for turnover (Models 1 and 2, respectively). \( t \)-statistics are reported in parentheses, and *** denotes 1% statistical significance. See Appendix C for variable description.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 2a</th>
<th>Model 2b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diffusive-var</td>
<td>-1.8707***</td>
<td>0.0225</td>
<td>-</td>
<td>-5.1321***</td>
</tr>
<tr>
<td></td>
<td>(-4.14)</td>
<td>(0.04)</td>
<td>-</td>
<td>(-7.27)</td>
</tr>
<tr>
<td>Jump-var</td>
<td>4.2548***</td>
<td>5.1547***</td>
<td>5.13***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(7.84)</td>
<td>(8.30)</td>
<td>(7.27)</td>
<td>-</td>
</tr>
<tr>
<td>Total-var</td>
<td>-</td>
<td>-</td>
<td>0.0225</td>
<td>5.1547***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.02)</td>
<td>(5.67)</td>
</tr>
<tr>
<td>( \ln(size) )</td>
<td>-0.0081***</td>
<td>-0.0075***</td>
<td>-0.0075***</td>
<td>-0.0075***</td>
</tr>
<tr>
<td></td>
<td>(-9.86)</td>
<td>(-11.55)</td>
<td>(-11.70)</td>
<td>(-11.70)</td>
</tr>
<tr>
<td>Turnover</td>
<td>-</td>
<td>-0.0015***</td>
<td>-0.0015***</td>
<td>-0.0015***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(-5.44)</td>
<td>(-3.43)</td>
<td>(-3.43)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.1196***</td>
<td>0.1136***</td>
<td>0.1136***</td>
<td>0.1136***</td>
</tr>
<tr>
<td></td>
<td>(10.70)</td>
<td>(12.57)</td>
<td>(11.98)</td>
<td>(11.98)</td>
</tr>
<tr>
<td>Average-( R^2 )</td>
<td>48%</td>
<td>50%</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Observations</td>
<td>44,171</td>
<td>44,171</td>
<td>44,171</td>
<td>44,171</td>
</tr>
</tbody>
</table>
Table 5: **CONTROLLING FOR INFORMATION ASYMMETRY.** This table reports estimation results for Equation (5) when controlling for asymmetric information. Our proxy for information asymmetry is the probability of informed trade (PIN). PIN is based on the imbalance between buy and sell orders among investors. These measures are obtained from Stephen Brown’s website and are based on Brown and Hillegeist (2007). The results in the first column are based on $Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t}^d + \beta_2 V_{i,t}^l + \beta_3 \ln(size_{i,t}) + \beta_4 PIN_{i,t} + \epsilon_{i,t}$, when regressing this model on all firm years in our data. Columns 2-6 report estimation results for $Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t}^d + \beta_2 V_{i,t}^l + \beta_3 \ln(size_{i,t}) + \epsilon_{i,t}$ applied to each information asymmetry quintile separately from low to high. $t$-statistics are reported in parentheses, and *** denotes 1% statistical significance. For further details see Section 5.4.

<table>
<thead>
<tr>
<th>PIN Rank</th>
<th>All</th>
<th>Low</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jump var</td>
<td>4.367***</td>
<td>6.646***</td>
<td>3.386***</td>
<td>2.323***</td>
<td>3.044***</td>
<td>6.303***</td>
</tr>
<tr>
<td></td>
<td>(5.91)</td>
<td>(4.16)</td>
<td>(4.42)</td>
<td>(5.58)</td>
<td>(7.11)</td>
<td>(5.96)</td>
</tr>
<tr>
<td>Diffusive var</td>
<td>-0.748</td>
<td>0.593</td>
<td>-1.005</td>
<td>-0.635</td>
<td>-1.286***</td>
<td>3.867</td>
</tr>
<tr>
<td></td>
<td>(-0.80)</td>
<td>(0.58)</td>
<td>(-1.22)</td>
<td>(-0.69)</td>
<td>(-2.42)</td>
<td>(1.71)</td>
</tr>
<tr>
<td>ln(size)</td>
<td>-0.007***</td>
<td>-0.007***</td>
<td>-0.005***</td>
<td>-0.004***</td>
<td>-0.004***</td>
<td>-0.010***</td>
</tr>
<tr>
<td></td>
<td>(-10.91)</td>
<td>(-12.65)</td>
<td>(-12.75)</td>
<td>(-10.06)</td>
<td>(-13.79)</td>
<td>(-8.58)</td>
</tr>
<tr>
<td>PIN</td>
<td>0.023***</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(10.35)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Constant</td>
<td>0.092***</td>
<td>0.112***</td>
<td>0.075***</td>
<td>0.071***</td>
<td>0.070***</td>
<td>0.149***</td>
</tr>
<tr>
<td></td>
<td>(10.65)</td>
<td>(12.23)</td>
<td>(12.73)</td>
<td>(10.43)</td>
<td>(14.41)</td>
<td>(8.93)</td>
</tr>
<tr>
<td>Average-$\overline{R^2}$</td>
<td>0.52</td>
<td>0.52</td>
<td>0.47</td>
<td>0.45</td>
<td>0.46</td>
<td>0.49</td>
</tr>
<tr>
<td>Observations</td>
<td>38,355</td>
<td>7,675</td>
<td>7,672</td>
<td>7,670</td>
<td>7,672</td>
<td>7,666</td>
</tr>
</tbody>
</table>
Table 6: **BID-ASK SPREADS AND RELATIVE SHARE OF JUMP COMPONENT: BY TURNOVER RATE.** We first sorted all stocks in each year into five different portfolios, from low to high. Then, for each portfolio level, we repeated our second method of double sorting on total variance and jump-driven variance and then averaging across all years and all total volatility ranks \( k \) per jump rank. This process was carried out for each of the five turnover portfolios separately. Then, for each jump portfolio level and turnover level, we calculated average bid-ask spreads in period \( t + 1 \). We also report the differences in bid-ask spreads between the highest and lowest portfolios and their \( t \)–statistics.

<table>
<thead>
<tr>
<th>Jump</th>
<th>Low</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>High</th>
<th>High-Low</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Turnover</td>
<td>.0354</td>
<td>.0384</td>
<td>.0389</td>
<td>.0424</td>
<td>.0479</td>
<td>.0125</td>
<td>10.73</td>
</tr>
<tr>
<td>2</td>
<td>.0174</td>
<td>.0201</td>
<td>.0213</td>
<td>.0227</td>
<td>.0248</td>
<td>.0074</td>
<td>10.08</td>
</tr>
<tr>
<td>3</td>
<td>.0083</td>
<td>.0103</td>
<td>.0107</td>
<td>.0126</td>
<td>.0151</td>
<td>.0068</td>
<td>13.19</td>
</tr>
<tr>
<td>4</td>
<td>.0050</td>
<td>.0058</td>
<td>.0059</td>
<td>.0071</td>
<td>.0088</td>
<td>.0038</td>
<td>10.76</td>
</tr>
<tr>
<td>High Turnover</td>
<td>.0040</td>
<td>.0044</td>
<td>.0044</td>
<td>.0052</td>
<td>.0066</td>
<td>.0026</td>
<td>8.26</td>
</tr>
</tbody>
</table>
Table 7: LIQUIDITY RISK – $\beta^{1L}$, $\beta^{2L}$ AND $\beta^{3L}$. This table reports regression results for Equation (8): $\beta_{k,i,t} = \alpha + \gamma_1 V_{i,t}^d + \gamma_2 V_{i,t}^j + \gamma_3 \ln(\text{size}_{i,t}) + \epsilon_{i,t}$, where $k = 1L, 2L, 3L$. This equation measures the effects jump and diffusive volatility have on $\beta^{1L}$, $\beta^{2L}$ and $\beta^{3L}$, when they are all obtained from a simple covariances measure as specified in Equation 6. $t$–statistics are reported in parentheses, and *** denotes 1% statistical significance.

<table>
<thead>
<tr>
<th></th>
<th>$\beta^{1L} = \text{Cov}(L^i, L^M)$</th>
<th>$\beta^{2L} = \text{Cov}(R^i, L^M)$</th>
<th>$\beta^{3L} = \text{Cov}(L^i, R^M)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duffusive Var</td>
<td>-26.546***</td>
<td>-537.760***</td>
<td>-0.262</td>
</tr>
<tr>
<td></td>
<td>(-4.65)</td>
<td>(-5.11)</td>
<td>(-0.22)</td>
</tr>
<tr>
<td>Jump Var</td>
<td>61.460***</td>
<td>93.824***</td>
<td>5.914***</td>
</tr>
<tr>
<td></td>
<td>(9.13)</td>
<td>(2.27)</td>
<td>(7.74)</td>
</tr>
<tr>
<td>$\ln(\text{size})$</td>
<td>-0.090***</td>
<td>-0.063***</td>
<td>-0.005***</td>
</tr>
<tr>
<td></td>
<td>(-14.32)</td>
<td>(-7.11)</td>
<td>(-6.18)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.564***</td>
<td>1.305***</td>
<td>0.080***</td>
</tr>
<tr>
<td></td>
<td>(14.05)</td>
<td>(10.81)</td>
<td>(6.60)</td>
</tr>
</tbody>
</table>
Table 8: CHARACTERISTICS OF $\beta^{2L}$. This table reports regression results for $\psi_i'$ in Equation (10): $e_{i,t} = \psi_0 + \psi_1 L^M_t + \psi_2 Z_{i,t-1} L^M_t + v_{i,t}$, which in return determines $\beta^{2L}_{i,t}$ in Equation (9): $\beta^{2L}_{i,t} = \psi_1 + \psi'_2 Z_{i,t-1}$. Following Pastor and Stambaugh (2003) this specification determines the effect different characteristics in $Z_{i,t-1}$ have on the sensitivity of stock returns to market liquidity, $\beta^{2L}_{i,t}$. For market liquidity factors we use the Sadka (2006) Variable-Permanent and Fixed-Transitory factors. $t-$statistics are reported in parentheses, and 1% and 10% statistical significance levels are denoted by *** and *, respectively. For more details see Equation (10).

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vector $\psi_1$</strong></td>
<td></td>
</tr>
<tr>
<td>Variable-Permanent Liquidity Factor</td>
<td>0.14***</td>
</tr>
<tr>
<td></td>
<td>(4.24)</td>
</tr>
<tr>
<td>Fixed-Transitory Liquidity Factor</td>
<td>5.12***</td>
</tr>
<tr>
<td></td>
<td>(9.84)</td>
</tr>
<tr>
<td><strong>Vector $\psi'_2$</strong></td>
<td></td>
</tr>
<tr>
<td>Jump $\times$ Variable Factor</td>
<td>81.61***</td>
</tr>
<tr>
<td></td>
<td>(3.26)</td>
</tr>
<tr>
<td>Jump $\times$ Fixed Factor</td>
<td>9348.29***</td>
</tr>
<tr>
<td></td>
<td>(29.47)</td>
</tr>
<tr>
<td>Diffusion $\times$ Variable Factor</td>
<td>-112.06*</td>
</tr>
<tr>
<td></td>
<td>(-1.84)</td>
</tr>
<tr>
<td>Diffusion $\times$ Fixed Factor</td>
<td>1229.87</td>
</tr>
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<td></td>
<td>(1.57)</td>
</tr>
<tr>
<td>Constant</td>
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</tr>
<tr>
<td></td>
<td>(2.09)</td>
</tr>
</tbody>
</table>