considerations are relevant to reforms currently being implemented to the regulatory environment in the EU and recently discussed in the US. 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. The current administration in the White House is leading a similar initiative in the US.[4] These steps can have important consequences for the structure of volatility and 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, reduce the jump component of volatility, and improve liquidity.

The remainder of this paper is organized as follows. Section 2 describes our hypothesis development and related literature. Section 3 discusses the research design and results for the analysis related to the firms' information environment and the structure of volatility. Section 4 discusses the research design and results for the analysis related to the structure of volatility and liquidity. Section 5 concludes.

2 Related Literature and Hypothesis Development

2.1 The Firm's Information Environment and Volatility Structure

A large existing literature examines the link between disclosure, the firm's information environment, and liquidity. Papers in this literature find that increased disclosure and more transparent information environments improve liquidity (e.g., Welker, 1995; Leuz and Verrecchia, 2000; Kelly and Ljungqvist, 2012; Balakrishnan et al., 2014). Empirically, these papers examine how various disclosure and information environment measures affect liquidity measures such as bid-ask spreads, volatility, and trading volume. A related stream of literature examines the effect of disclosure on the cost of capital, based on the idea that improvements in liquidity result in lower cost of capital (e.g., Armstrong et al., 2010; Francis et al. 2005; Hail and Leuz, 2006). Motivated by theoretical models such as Diamond (1985) and Diamond and Verrecchia (1991), the underlying assumption in both literature streams is that improved disclosure reduces information asymmetry and hence improves liquidity.

Motivated by recent developments in the asset pricing literature, in this paper we propose a new channel through which disclosure and the firm's information environment can affect

[4] https://www.wsj.com/articles/trump-directs-sec-to-study-six-month-reporting-for-public-companies-1534507058?mod=article_inline&mod=djemCFO_h

liquidity based on the structure of volatility. In addition to affecting the level of information asymmetry, the firm's information environment determines a firm's information arrival rates, or the pace at which information arrives to the market. Stocks in 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). Consequently, the firm's information environment affects the firm's volatility structure, or the relative level of the jump versus diffusive components of volatility. In other words, even when holding the amount of information the firm releases constant, the rate at which the information is released has an effect on the level of jump volatility. For a given amount of information, more transparent firms with increased disclosure levels experience a more continuous flow of information to the market and hence lower levels of jump volatility. As discussed in more detail below, the relation between the firm's information environment and jump volatility offers an alternative channel through which the information environment can affect liquidity. Our first prediction is as follows:

H1: More transparent firms with increased disclosure levels experience lower levels of jump volatility

Figure 1, Panel A, provides some intuition for our prediction. The stocks in the example experience the same total returns, and total volatility, but very different price paths. So while the total amount of information released is the same for both stocks, the information in "Jump" is released all at once, while the information in "Diffusion" is released in a more continuous manner. The more transparent information environment in "Diffusion" results in lower jump volatility levels.

Hypothesis H1 is related to two additional literature streams. The first examines the association between disclosure frequency and liquidity (e.g., Botosan and Harris, 2000; Van Buskirk, 2011; Fu et al., 2012). These papers find mixed results. Botosan and Harris (2000) find that decreases in liquidity motivate firms to increase segment disclosure frequency. Van Buskirk (2011) finds no relation between bid-ask spreads, depth, and more frequent disclosure of monthly sales figures. In contrast, Fu et al. (2012) find that increased financial reporting frequency is associated with lower bid-ask spreads and lower price impact levels. These papers motivate their analysis by articulating how disclosure frequency impacts information asymmetry and thus liquidity. They further highlight that disclosure frequency has an ambiguous effect on information asymmetry. However, disclosure frequency also affects information arrival rates or jump volatility which in turn affects liquidity. An increase in information arrival rates has an unambiguous negative relation with jump volatility, and hence a positive relation with liquidity. By employing the structure of volatility in our analysis we are able to take a step towards disentangling these two effects.

The second related literature stream examines the association between disclosure and total volatility. Prior research suggests that volatility is a characteristic of the information environment managers care about. For example, total volatility has been shown to decrease liquidity (Chordia et al., 2005) and increase the likelihood of litigation (Kim and Skinner, 2012). Therefore, managers may make disclosure choices to reduced volatility (e.g., Graham et al., 2005). However, the empirical evidence in this literature is mixed. Bushee and Noe (2000) find that increased disclosure levels that attracts transient institutional investors results in increased volatility. Rogers et al. (2009) find that unbundled earnings forecasts are associated with increased implied volatility levels. In contrast, Billings et al. (2015) finds that firms issue more bundled earnings guidance in response to increased volatility levels, and that these disclosures result in a reduction in volatility. Our analysis differs from the analysis in this literature because we employ the structure of volatility in our analysis. This allows us to isolate how disclosure and the information environment affects jump volatility, which is the component of volatility that affects liquidity.

2.2 Volatility Structure and Liquidity

As a starting point, we note that according to microstructure theory illiquidity, or bid-ask spreads, are determined by two economic forces (see Figure 2). The first is the level of information asymmetry that determines the adverse selection component of the bid-ask spread (Glosten and Milgrom, 1985; Kyle, 1985). The second is the inventory risk that the market maker faces (Stoll, 1978a; Amihud and Mendelson, 1980). The role of the structure of volatility, and jump volatility in particular, in determining liquidity arises from the link between jump volatility and the inventory risk the market maker faces. This link is independent of the level of information asymmetry in the firm.

The literature on jumps highlights two facts that lead to the predictions for how each volatility component affects liquidity. These facts are directly linked to the theory of liquidity, which emphasizes the risks market makers face in determining liquidity and particularly inventory risk. 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.[5]

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 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 as they can match the order flow much more easily and consequently increase liquidity (E.g., Tinic and West, 1972; Stoll, 1978a). This line of reasoning entails a negative association between diffusive volatility and illiquidity, due to increased turnover. Taken together, these lines of reasoning lead us to our second prediction:

H2: There is a positive relation between jump volatility and illiquidity measures such as bid-ask spreads. In contrast, there is a negative relation between diffusive volatility and illiquidity.

We further note that according to theory the predicted relation in H2 is independent of the relation between the level of information asymmetry and the adverse selection component of the bid-ask spread. We test his theory empirically by controlling for the level of information asymmetry in our analysis.

[5] See Longstaff (1995, 2014), who models the implications of a similar aspect to illiquidity.

3 The Firm's Information Environment and Volatility Structure

3.1 Research Design

3.1.1 Estimating the Jump-Diffusion Process

In our analysis, we follow a standard framework to model the jump-diffusion processes. We apply estimation procedures used, validated, and empirically tested in numerous prior studies (e.g., Ait-Sahalia, 2004; Yu, 2007).[6] 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 λ, and a random jump size Z_t which is distributed lognormally with mean α and variance γ^2. The stock return dynamics are described by the following stochastic differential equation:

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

where μ and σ 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.[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,

$$\begin{aligned} V^d &= \sigma^2 t \\ V^j &= \lambda \left(\alpha^2 + \gamma^2\right) t \end{aligned} \tag{2}$$

which allows us to calculate the values of the variance components. Total return variance is just the sum of the two components,

$$V = V^d + V^j. \tag{3}$$

[6] 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).

[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.

Applying maximum likelihood estimation (ML), we calibrate the model based on historical stock return data and obtain a vector of parameter estimates $\theta_i^t = (\mu_i^t, \sigma_i^t, \lambda_i^t, \alpha_i^t, \gamma_i^t)$ for each stock i estimated over period t. Based on θ_i^t, we then calculate $V_{i,t}^d$ and $V_{i,t}^j$, that is, the respective diffusive and jump variance components of total variance.[8] For a more detailed description of our framework, estimation procedure, and related references, see Appendix A. While the jump and diffusion components, $V_{i,t}^j$ and $V_{i,t}^d$, are measures of variance, following prior literature we refer to variance and volatility interchangeably when discussing the structure of volatility.

3.1.2 The information environment and jump volatility

To examine how the information environment affects liquidity through the structure of volatility, we begin by examining the relation between various measures of disclosure and the firm's information environment, and jump volatility. Specifically we employ the following regression:

$$V_{i,t}^j = \beta_0 + \beta_1 Disclosure_{i,t} + \beta_2 Controls_{i,t} + Firm\_FE_i + Year\_FE_t + \varepsilon_{i,t} \qquad (4)$$

where the dependent variable is our estimate of jump volatility. $Disclosure_{i,t}$ equals one of three measures. First, we define the variable $Forecaster_{i,t}$ which equals one if the firm issues earnings guidance on a regular basis following the definition in Rogers et al. (2009), and zero otherwise. Second, we employ the number of forecasts issued by the firm over the year ($Num\_Forecasts_{i,t}$). As our third measure we use the dispersion in analyst forecasts ($Dispersion_{i,t}$) as an overall measure of the firm's information environment. Prior research employs dispersion as a measure of increased uncertainty (e.g., Palmrose et al., 2004; Graham et al., 2008). We hypothesize that firms with increased levels of uncertainty experience less transparent information environments. Therefore, we expect $\beta_1 < 0$ for our first two forecast based measures, and $\beta_1 > 0$ for our dispersion measure.

The first control variable we add is the relative bid-ask spread to control for the possibility that variation in information asymmetry drives variation in spreads which can mechanically result in variation in jump. Next, we proceed to add various control variables that prior research has shown to be associated with firms' disclosure choices, that may also relate

[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.

to variation in jump volatility (e.g., Lang and Lundholm, 1993; Skinner, 1994; Leuz and Verrecchia, 2000; Miller, 2002). Specifically, we include prior returns, return on assets, and whether the firm experiences a loss to control for differences in firm performance. We include earnings volatility to capture firm-level uncertainty that may affect manager's disclosure activities. We also control for the following additional variables that prior literature has found to be associated with a firm's disclosure policy: firm size, leverage, market-to-book, institutional ownership, and the number of analysts following the firm. Moreover, all our regressions include firm and year fixed-effects to control for unobservable time invariant characteristics that may determine variation in firms' disclosure choices and variation in jump volatility, as well as time trends in firm's disclosure and jump volatility levels. Finally, we control for diffusion to alleviate concerns that our results merely reflect an association between disclosure, the firm's information environment, and total volatility. All the variables are described in detail in Appendix B

To provide more causal evidence related to how the information environment affects jump volatility we examine how brokerage house closures, which result in an exogenous drop in analyst coverage and hence an exogenous change in the flow of information to the market, affect jump volatility. We follow Kelly and Ljungqvist (2012) and identify firm-years where there was a brokerage house closure that resulted from either a stand-alone brokerage house closures or a merger.[9] We compare changes in jump volatility in the two years following the closures for the affected firm-year observations, relative to the unaffected firm-year observations.[10] To clearly identify affected and unaffected firm-years we only retain firm-years following the closure, and firm-years with no closures in the past three years. This process removes contaminated firm-years that could be construed as both pre and post closures, or both affected and unaffected. Specifically, we estimate the following model:

$$V_{i,t}^{j} = \beta_0 + \beta_1 Treat * Post_{i,t} + \beta_2 Controls_{i,t} + Firm\_FE_i + Year\_FE_t + \varepsilon_{i,t} \qquad (5)$$

The dependent variable is our estimate of jump volatility. $Treat_i$ is an indicator variable that receives the value of one for all firms that experience a closure at some point in the sample, and zero otherwise. $Post_{i,t}$ is an indicator variable that receives the value of one for all firms that experience a closure in year_t or year_{t-1}, and zero otherwise. Therefore, $Treat_i * Post_{i,t}$ is an indicator variable that takes the value of one for all firms that experience a closure in

[9] We use the data employed in Rozenbaum (2014) starting in 2002. We thank Oded Rozenbaum for providing his data.

[10] This horizon is comparable to the horizon employed by Balakrishnan et al., (2014). They employ four quarters before and after the closure, in addition to the quarter of the closure.

year_t or year_{t-1}, and zero for those that do not experience any closures in years $t, t-1$ and $t-2$. The main effects, $Treat/Post$, are subsumed by the firm and time fixed-effects and thus drop out. Similar to Balakrishnan et al. (2014) we control for size and the number of analysts following the firm. We further include the relative bid-ask spread, to control for variation in information asymmetry that results from the closure that can mechanically increase jump. Finally, we control for diffusion to alleviate concerns that our results merely reflect an increase in total volatility. We expect $\beta_1 < 0$.

As a counterfactual test, we reestimate the model using diffusion ($V^d_{i,t}$) as the dependent variable. If the brokerage house closures change the structure of volatility and increase volatility through jump volatility, we expect brokerage house closures to affect diffusion relatively less.

As an alternative analysis, we estimate model 5 only for firms that experience a closure at some point in our sample. This analysis alleviates concerns that differences between firms that experience closures, and firms that do not, are driving our results. All the variables are described in detail in Appendix B.

3.2 Empirical Analysis

3.2.1 Sample and Descriptive Statistics

We obtain daily stock prices, volume, shares outstanding, and market-capitalization for all stocks listed on the NYSE and NASDAQ between 2002–2012 from CRSP. 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 historical TAQ 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.

We eliminate all firm-years with less than 245 observations per year, and those with bid-ask spreads (percent) that are larger than 50% or negative. We also eliminate securities that do not have data on market capitalization for year t in the CRSP database; this excludes non-stock securities listed on exchanges. This process results in 9,088 unique stocks in the period 2002–2012, for a total of 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 $\theta^t_i = \left(\mu^t_i, \sigma^t_i, \lambda^t_i, \alpha^t_i, \gamma^t_i\right)$ 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 (V_i^t as specified in Equation (3)) with the realized daily return-variance, measured over the corresponding year t. We denote the realized variance by $\widetilde{V}_i^t$. For more than 90% of our sample, the ratio $\frac{\widetilde{V}_i^t}{V_i^t}$ 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.

To finalize our estimation process, we eliminate all estimates with extreme values, that is, the highest and lowest 1% for all parameters of the vector θ_i^t. We also eliminate all observations that do not satisfy the condition $\frac{\widetilde{V}_i^t}{V_i^t} \in [0.8, 1.2]$.[11] After applying these additional filters, our final sample contains 55,558 stock-years observations. The average jump size α in our sample is 3% (in absolute values), and the average jump frequency λ is 16%. These estimates are comparable to estimates obtained in prior studies (e.g., Todorov and Bollerslev, 2010; Tauchen and Zhou, 2011).[12]

To create our final sample, for each firm-year we determine whether the firm issues earnings guidance on a regular basis, and the number of forecasts issued by the firm in a year, based on the data available in the CIG file in the First Call database. We collect data on the number of analyst forecasts issued and the dispersion of analyst forecasts from the summary file in the IBES database. Additional control variables are obtained from Compustat and Thompson Reuters. For the analysis related to management forecasts we end our sample in 2010, because the First Call database was discontinued in early 2011.

The descriptive statistics are reported in Table 1. Panel A reports overall average and quintile values for total variance, jump variance, and diffusive variance estimated using the model. Variance is computed for each firm i in year t using daily stock return data. The average total return variance across all years and stocks is around 0.11%, while the average jump and diffusive variances are around 0.065% and 0.044% respectively. Panel B reports overall average and quintile values for total volatility (standard deviation), jump volatility, and diffusive volatility, which equal the square root of the model implied variances. Average total return volatility across all years and stocks is around 2.9%. Average values for the diffusive and jump components are of the same order of magnitude, 1.8% and 2.0%, respectively, and their medians are around 1.7%.[13] Panel C reports summary statistics for

[11] This final elimination does not alter the inferences reported in this paper.

[12] While our starting sample of 55,558 observations remains constant across our tests, the actually number of observations in each table varies according to the variables employed and years included in each analysis.

[13] 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.

the remaining variables used in our analysis. The average level of bid-ask spreads is around 1.8%. Approximately 20% of the firms in our sample provide forecasts on a regular basis. The average number of forecasts issued by a firm in a year is close to 1.5. The mean level of dispersion in our sample is approximately 1.4% of price.

3.2.2 Disclosure and the Information Environment

The results for the disclosure related analysis are presented in Tables 2 and 3. Table 2 reports the results for our forecasting variable ($Forecaster_{i,t}$). The coefficient in column (1) is negative (-0.017) with a t-statistic of -10.30. This result is consistent with H1 and shows that firms that issue management forecasts on a regular basis, which have a relatively more continuous flow of information, experience lower levels of jump volatility. On average, forecasting firms have jump volatility levels that are lower by 26% of the sample average. We find a similar effect after controlling for the level of bid-ask spreads. The coefficients remain negative and significant after we include a host of control variables, including the level of diffusion. Coefficients in these specifications range from -0.0052 to -0.0043 with t-statistics ranging from -2.75 to -3.24.

Table 3 report results for the number of forecasts issued by the firm ($Num\_Forecasts_{i,t}$). The results in this analysis mirror the results in Table 2. The coefficient in column (1) is negative (-0.012) with a t-statistic of -10.44. This result is also consistent with H1. Firms that issue more forecasts throughout the year and have a relatively more continuous flow of information experience lower levels of jump volatility. Once again, the coefficients remain negative and significant across the specifications with coefficients ranging from -0.0022 to -0.01, with t-statistics ranging from -2.18 to -9.13. In terms of economic magnitude, a one standard deviation increase in the number of forecasts issued, reduces jump volatility by between 10-47% of the sample average, depending on the specification employed.

Table 4 report results when we use analyst forecast dispersion ($Dispersion_{i,t}$) as our measure of the firm's information environment. We find a strong positive relation between the relative dispersion in analyst forecasts and the level of jump volatility in the firm. To the extent that firms with increased forecast dispersion are less transparent and experience a less continuous flow of information to the market, these results support our findings in Tables 2 and 3.

3.2.3 Brokerage House Closures

The results related to equation(5) are presented in Table 5. In Panel A, the coefficient for the variable $Treat * Post$ in columns (1) - (3) is positive and significant across the specifications, after controlling for bid-ask spreads and diffusion. The coefficients range from 0.0041 to 0.0047, and t-statistics ranging from 2.87 to 3.34. These results provide more causal evidence related to the relation between the information environment of the firm and jump volatility. Firms that experience an exogenous drop in information arrival rates such that information arrives in a more bulky and discontinuous manner, due to an exogenous decline in analyst coverage, experience increases in jump volatility. We find similar results in Panel B, when we limit our sample to firms that experience at least one brokerage house closure in our sample.[14]

To validate that our results reflect a change in the structure of volatility, in columns (4)-(5) we replace the dependent variable jump (V^j) with diffusion (V^d). We fail to find similar increases in diffusion following brokerage house closures. Once again, we find similar results in Panel B, when we limit our sample to firms that experience at least one brokerage house closure in our sample. Taken together, the results in Table 5 provide causal evidence on the relation between the information environment and jump volatility, independent from the link between the information environment and information asymmetry.

4 Volatility Structure and Liquidity

4.1 Research Design

We estimate Fama-MacBeth regressions to formally test how the different components of variance relate to 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 following cross-section regression year-by-year

$$Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t} + \beta_2 \ln(size)_{i,t} + \varepsilon_{i,t} \tag{6}$$

where the dependent variable $Liq_{i,t+1}$ denotes the relative bid-ask spread (in percent) for stock i in the following year $t+1$.[15] The explanatory variables on the right-hand side include total variance $V_{i,t}$, the log of the market capitalization $\ln(size)_{i,t}$, 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,

[14] Our sample includes 2,300 treated firms and 6,270 treated firm-years.

[15] 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.

following the Fama-MacBeth method. Therefore this procedure yields a vector of estimates $\beta = \left(\beta_0, ..., \beta_{1+J}\right)$ that characterizes the variables' effect on liquidity.[16]

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

$$Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t}^d + \beta_2 V_{i,t}^j + \beta_2 \ln(size)_{i,t} + \varepsilon_{i,t} \tag{7}$$

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 (6).

As discussed in the introduction, because the structure of volatility is governed by the information environment of the firm, the link between jump and liquidity 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. First, we simply add a control variable to Equation (7) to account for the level of information asymmetry. Second, we sort our sample into five quintiles of information asymmetry and re-estimate Equation (7) 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 their paper they compute PINs using the Venter and De Jong (2006) model to extend the Easley et al. (1997) model.

4.2 Empirical Analysis

4.2.1 Univariate Analysis - Sorted Portfolios

As a first step we provide univariate evidence using a portfolio framework. We examine how each volatility component relates to illiquidity while controlling for the remaining volatility

[16] 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).

component. In Table 6, Panel A, we sort all stocks in our sample for each year t on their diffusion-driven variance portion V^d and form five equally weighted portfolios. The first quintile portfolio contains stocks with the lowest diffusive volatility component for a given year, and the fifth quintile contains stocks with the highest diffusive volatility component. We denote these portfolios by $d = 1, ..., 5$. Then, for each year t, we further sort each of the five portfolios $d = 1, ..., 5$ on their jump-driven variance component V^j to form additional five equally weighted sub-portfolios per portfolio rank d. The first quintile sub-portfolio contains stocks with the lowest V^j and the fifth quintile sub-portfolio contains stocks with the highest V^j. This way, we create for each year t, and diffusive portfolio rank d, five subgroups of stocks ranked from 1-5 sorted on V^j. We denote these sub-portfolios by $d_j = 1, ..., 5$. We then calculate average bid-ask spreads for each sub-portfilo in year $t + 1$.

As seen in Panel A, there is a strong positive relation between bid-ask spreads and the jump volatility ranking, while holding diffusive volatility levels fixed. This relation exists 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 points, with t-statistics ranging from 18.94 to 27.57 indicating high statistical significance.

In Panel B of Table 6 we repeat the same procedure the other way around. That is, we sort all stocks on the jump variance component V^j and then further sort each jump portfolio $j = 1, ..., 5$ on the diffusive variance component. This way, we create for each year t, and jump portfolio rank j, five sub-portfolios ranked from 1–5 sorted on V^d. We denote these sub-portfolios 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 from this analysis. As seen in Panel B, there is now a negative relation between bid-ask spreads and the ranking of diffusive volatility, controlling for jump volatility levels. 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 t-statistics ranging from -7.76 to -13.10. The only exception is for the highest jump portfolio which exhibits a very small and insignificant difference in bid-ask spreads between its high and low diffusive volatility portfolios.

4.2.2 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. The first column in Table 7 reports Fama-MacBeth regression results based on the model specified in Equation (6). Total variance indeed has a positive and significant impact on bid-ask spreads, with a coefficient estimate of 2.19 and t-statistic of 5.52. Market capitalization also has a negative and statistically significant effect. These findings are consistent with prior studies that found a positive relation between volatility and illiquidity costs (e.g., Stoll, 1978b, 2000; Pastor and Stambaugh, 2003).

4.2.3 Fama-MacBeth Regressions: Volatility Components and Illiquidity

In the next step, we decompose total volatility into its jump and diffusive driven components. The second column of Table 7 reports Fama-MacBeth regression results for the regression specified in Equation (7), which explicitly models separate effects for each component. The estimated effects of jump and diffusive volatilities are very different. The jump-driven variance coefficient is 4.25 compared to -1.87 for the diffusive one. Both coefficients 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 40 basis points, whereas an equivalent increase in the diffusive volatility component decreases bid-ask spreads by approximately 10 basis points. Firm size maintains a very similar effect compared to those obtained for total volatility. Finally, the Fama-MacBeth average $\overline{R}^2$ is between 48% and 49%, indicating that the model has strong explanatory power.

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, for convenience and ease of presentation 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 7, using Models A and B respectively. The coefficient estimates in Model A and B match their implied values from the coefficient estimates in the original specification.[17]

In summary, our results indicate that the structure of volatility significantly matters for bid-ask spreads beyond the raw levels of volatility. While the jump-driven volatility component drives the positive relation between volatility and illiquidity, the diffusive component has an opposite relation.

[17] 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 $y = (\beta - \alpha) x_2 + \alpha x_3$.

4.2.4 Controlling for Information Asymmetry

In our next analysis we examine the relation between the structure of volatility and liquidity controlling for information asymmetry. The results from these tests are presented in Table 8. The first column presents estimation results for Equation (7) 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 7). Columns 2-6 present estimation results for Equation (7) 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. 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.

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.

4.2.5 Causal Evidence for the Relation between the Information Environment and Liquidity Driven by Jump Volatility

In section 3.2.3 (Table 5) we provided casual evidence that more opaque information environments result in higher levels of jump volatility. Specifically, we show that firms that experience an exogenous drop in information arrival rates, due to an exogenous decline in analyst coverage, experience increases in jump volatility. In this section, we use the same shock to analyst coverage to employ a two-stage shock based Instrumental Variable (IV) design with which to estimate the relation between the information environment and liquidity that is driven by jump volatility (see Atanasov and Black, 2016, for a survey on shock based IV designs). A shock based IV design is useful when there is a particular channel through which the causal relation between two variables is expected. In our setting, we expect that a shock to the information environment will affect liquidity through the channel of jump volatility.

To operationalize the shock based IV design we employ the analysis presented in Table 5 as a first stage regression and estimate the effect of the shock to the information environment on jump volatility. The results in Table 5 show that the shock to the information environment, which results from the exogenous drop in analyst coverage, has a strong effect on jump volatility. Using the variable $Treat * Post$ as an instrument for jump, we estimate the predicted value of jump using the specification in column (3) of Table 5, excluding the bid-ask spread variable. We label the predicted value $Jump\_Hat$. In the second stage regression, we regress the newly constructed $Jump\_Hat$ variable and all the controls variables used in the first stage on illiquidity. Specifically, we estimate the following model where $\hat{V}^j$ is the predicted value $Jump\_Hat$. Following the prior analysis equation (8) is estimated using Fama-MacBeth regressions.

$$Liq_{i,t+1} = \beta_0 + \beta_1 \hat{V}^j_{i,t} + \beta_2 V^d_{i,t} + \beta_3 Controls_{i,t} + \varepsilon_{i,t} \tag{8}$$

$Jump\_Hat$ is the change in jump that results form the exogenous change in analyst following. Therefore, the coefficient β_1 represents an estimate for the change in liquidity that results only through the effect of the drop in analyst coverage on jump volatility, as opposed to through an alternative channel.[18]

The results from the second stage are presented in Table 9. The coefficient on $Jump\_Hat$ is positive and significant (40.82 with a t-statistic of 3.59).[19] This result suggests that a deterioration in the information environment resulting in information arriving in a more bulky and discontinuous manner causally decreases liquidity through the channel of jump volatility.

4.2.6 Testing for Reverse Causality - Turnover

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.

[18] One potential concern is that the change in jump that resutls from the breokerage house clsoures is highly correlated with the change in information asymmetry that results from the brokerage house closures. However, the results in Table 5 show that the relation between the closures and jump is not affected by the inclusion of spreads as a control variable.

[19] In untabulated results, we confirm that the coefficient for size is negative and significant similar to the result in Table 7 when the number of analysts following the firm is removed from the regression.

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 turnover portfolio, we double sort on total volatility and jump-driven volatility creating 25 portfolios for each turnover level. To control for total volatility, we calculate average bid-ask spreads per jump level across all five total volatility buckets. Therefore, we have a five-by-five portfolio ranking sorted on turnover level and jump-driven volatility level while controlling for total volatility. We report the results in Table 10.

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 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.

4.2.7 Turnover

Higher turnover rates reduce market-makers' inventory costs because they can better match the order flow and consequently increase liquidity (E.g., Tinic and West, 1972; Stoll, 1978a). As discussed earlier , diffusive volatility is associated with increased trading, while jump volatility is not (e.g., Giot et al., 2010). This fact entails that the negative association between diffusive volatility and illiquidity is mediated through the effect turnover has on illiquidity. This gives rise to a prediction that diffusive volatility should have no effect on illiquidity after controlling for turnover effects.

To test this prediction we repeat the regressions specified in Equations (6)-(7) this time explicitly accounting for turnover effects by including a turnover variable in these regressions. Table 11 reports estimation results for these regressions. The first column displays the results for the effect total variance has on bid-ask spreads. Under this specification, the coefficient estimate for total variance increases to 3.44 with a t-statistic of 6.02 (compared to 2.19 and 5.52 in Table 7, respectively). 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.

The second column in Table 11 reports the results for separating between the two volatility components. Under this specification the jump-driven variance coefficient increases to 5.15, while the diffusion-driven variance coefficient dramatically drops to 0.02 (compared to 4.25 and -1.87 in Table 7, respectively). Moreover, the t-statistic for the jump-component coefficient remains high (8.30) but for the diffusive component it drops to 0.04 (compared to 7.84 and -4.14 in Table 7, respectively). The turnover coefficient is negative, similar to that obtained for total volatility. These results confirm that the entire relation between diffusive volatility and illiquidity is indirect and it is completely driven by turnover, as predicted. In contrast, the relation between jump volatility and illiquidity is direct and unrelated to increased trading activity.

4.2.8 Crash Risk

We also verify that the dominant effect the jump component has on illiquidity is not driven by crash risk. In unreported results, we find that the dominance of the jump components is qualitatively the same for positive and negative average jump sizes (α). Similarly, when including a dummy variable for negative jumps to control for crash risk, its coefficient estimate is insignificant. This result is expected and consistent with the way market-makers operate, as they hold non-zero stock inventories in both directions, long and short, exposing them to price changes risk in both directions, for positive and negative price changes.

4.2.9 Volatility Components and Liquidity Risk

A number of studies have shown that liquidity levels are risky (e.g., Pastor and Stambaugh, 2003; Sadka, 2006).[20] 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

[20] Amihud and Mendelson (2015) review this literature, see additional references therein.

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 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 Sadka (2006). In untabulated results we find that jump and diffusive volatilities have very different effects. The interactions between the jump component and the 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 volatility 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.

5 Conclusions

In this paper, we propose and empirically investigate a new channel through which the information environment of the firm can affect liquidity. We propose that the information environment affects liquidity not only through information asymmetry, as documented in prior literature, but also through the structure of volatility and the distinct channel of the market maker's inventory risk (e.g., Johnson and So, 2018). This gives rise to an additional path, which is independent from information asymmetry, through which the information environment can affect liquidity, the cost of capital, and result in real effects.

We employ modern models for the structure of volatility to decompose total volatility into its jump and diffusive components. Volatility patterns generated by a discontinuous jump process (jump) arise from infrequent large isolated price changes while diffusive volatility (diffusion) arises from smooth continuous small price changes. Stocks in which information arrives in a more bulky and discontinuous way are more likely to be subject to jumps (Maheu and McCurdy, 2004). Consistently, we show that stocks with more transparent information environments and more frequent disclosures have lower jump volatility levels.

Specifically, we find that firms that issue earnings guidance on a regular basis, and firms that issue more earnings forecasts in a year, experience lower levels of jump volatility. These results are found after controlling for bid-ask spreads, the level of diffusion, and firm and year fixed-effects. The effect is economically significant. For example, a one standard deviation increase in the number of forecasts issued during the year decreases jump volatility between 10-47% of the sample average. We find similar results using analyst forecasts dispersion as a measure of the firm's information environment. To provide more causal evidence on the role of the information environment, we exploit the brokerage house closure setting employed by Kelly and Ljungqvist (2012) and Balakrishnan et al. (2014). We find that an exogenous drop in analyst coverage causally increases jump volatility.

The relation between the information environment and the structure of volatility has implications for liquidity. We show that jump volatility drives the positive relationship between volatility and illiquidity, while diffusive volatility has a negative relation. These relations are found at all levels of information asymmetry. These results are consistent with the idea that jump volatility increases the market maker's inventory risk which in turn decreases liquidity. In an effort to provide more causal evidence, we employ a two stage shock based instrumental variable design using the brokerage house closures as an instrument for jump. We continue to find a positive relation between jump and illiquidity using this approach.

This result suggests that a shock to the information environment resulting in information arriving in a more bulky and discontinuous manner causally decreases liquidity due to an increase in jump volatility.

The relation between jump volatility and liquidity is independent of the relation between information asymmetry and liquidity. Since the disclosure policy and information environment of the firm have a direct influence on the structure of volatility, disclosure can drive illiquidity trough the structure of volatility.

At the regulatory level, our study provides evidence that implementing accounting and disclosure policies that encourage more continuous flows of information may help increase liquidity. Such policies are likely to reduce the jump component of volatility, smooth potential surprises, and thus improve liquidity.

In closing, we note that causal terms we used to describe the mechanism through which the volatility components affect liquidity are purely inspired by the theoretical arguments that motivate our empirical study. 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 and in Section 2 provide the inspiration for our empirical investigation, which is significant in itself, particularly given the fact that no work has been done on this topic. Therefore, our findings also provide motivation for further developments of an explicit theoretical model, which we leave for future research.

Appendix A: Model and Estimation Method

Following Merton (1976), let S_t denote a stock price at time t on a filtered probability space $(\Omega, F, (F_t), P)$, 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 μ and σ^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 $\ln Z \backsim N(\alpha; \gamma^2)$ 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 θ is $\theta = (\mu, \sigma^2, \lambda, \alpha, \gamma^2)'$, where α and γ^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

$$V \equiv Var\left(\frac{S_t}{S_0}\right) = Var(\sigma W_t) + Var(J_t), \tag{9}$$

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

$$\begin{aligned} V^d &\equiv Var(\sigma W_t) \\ V^j &\equiv Var(J_t) \end{aligned}$$

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

$$\begin{aligned} V^d &= \sigma^2 t \qquad (10) \\ V^j &= \lambda\left(\alpha^2 + \gamma^2\right) t, \end{aligned}$$

which allow for easily calculating these values based on the parameter vector θ.

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 $f_{\Delta \ln S|\Delta N_t=0}$ 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

$$
\begin{aligned}
P(\Delta N_t &= 0) = 1 - \lambda \cdot \Delta t + o(\Delta t) \\
P(\Delta N_t &= 1) = \lambda \cdot \Delta t + o(\Delta t) \\
P(\Delta N_t &> 0) = o(\Delta t),
\end{aligned}
$$

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

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

where

$$
\begin{aligned}
m(k) &= \left(\mu - \sigma^2/2 - \lambda \cdot E(Z-1)\right) \Delta t + k \cdot a \\
v(k) &= \sigma^2 \cdot \Delta t + k \cdot \gamma^2,
\end{aligned}
$$

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

$$
\hat{\theta} = \arg\max_{\theta} \sum_{i=1}^{n} \ln f_{\Delta \ln S}(\Delta \ln s_i; \theta)
$$

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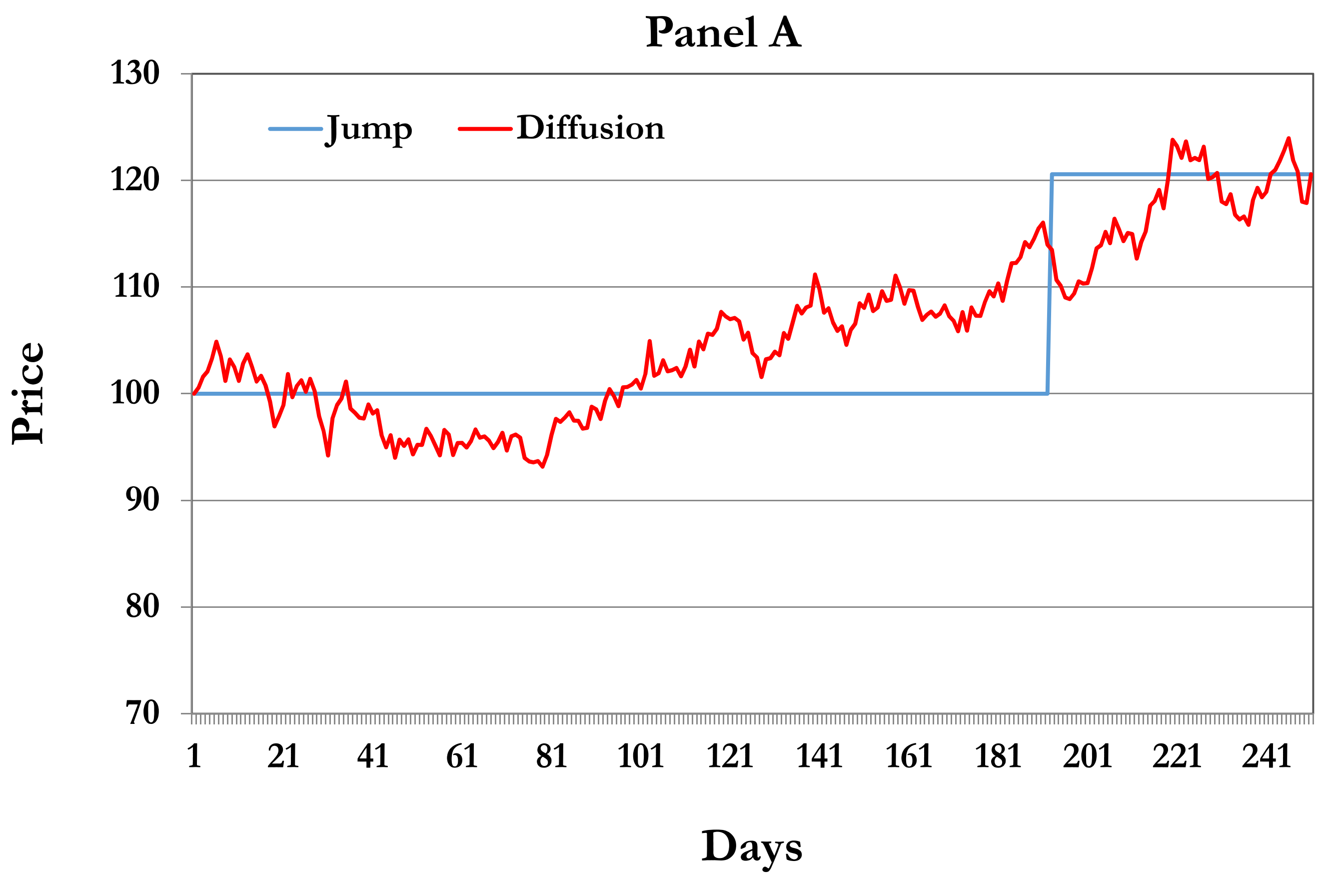
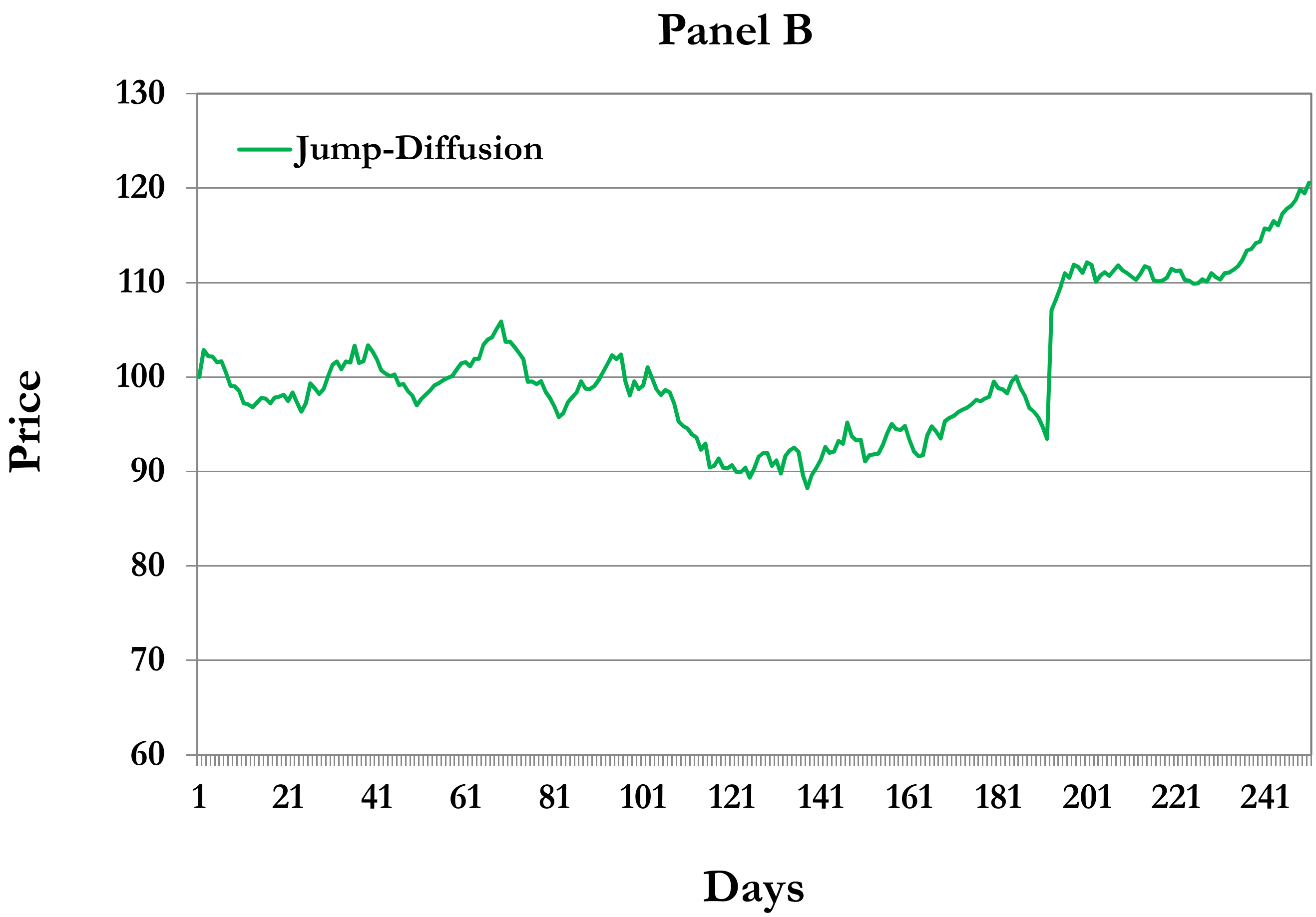
Figure 1

Panel A presents a simulated price path for two stocks. The total volatility of the stock Jump is 20%, resulting from one jump process. The total volatility of the stock Diffusion is also 20%, resulting from a diffusive process with no jumps. Panel A presents the price paths for each stock separately. Panel B presents the price path for a new stock, Jump-Diffusion, which is a combination of the two stocks.

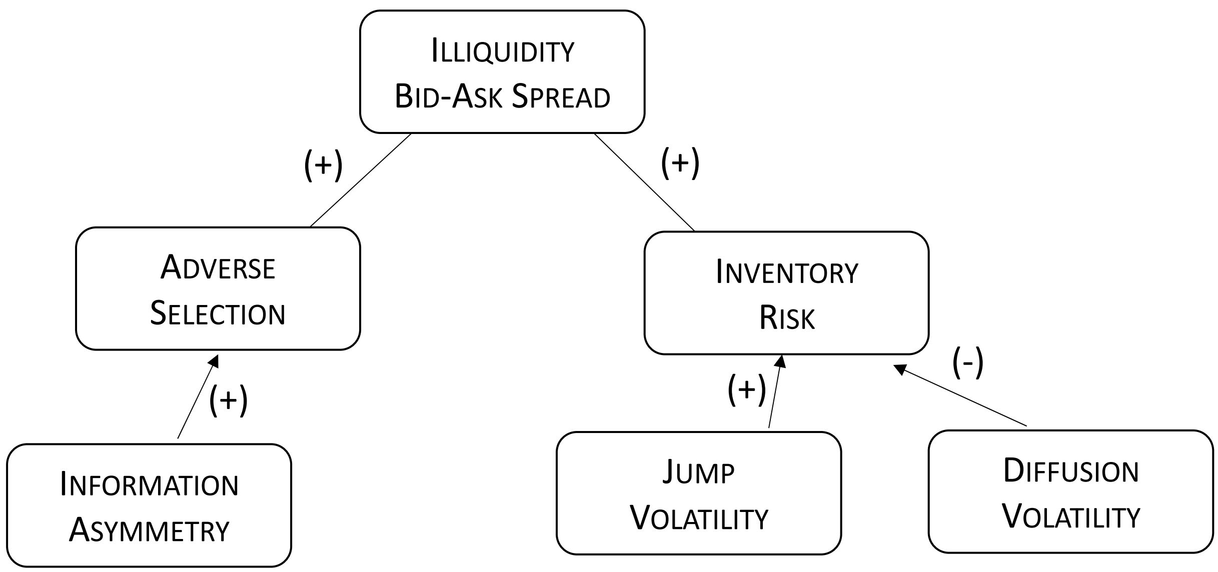




Panel B
Jump-Diffusion
130
120
110
100
90
80
70
60
Price
1
21
41
61
81
101
121
141
161
181
201
221
241
Days

Figure 2

This figure presents a conceptual sketch of the drivers of illiquidity or bid-ask spreads. The figure highlights that illiquidity is driven by both information asymmetry and inventory risk. Therefore, the effect of jump volatility on illiquidity presents an alternative channel that affects illiquidity, independent from the relation between information asymmetry and illiquidity.



Appendix B: Variable Definitions

Variable Name	*Description*
μ	• Constant parameter of the diffusion process representing the diffusive drift. • See Appendix A
σ	• Constant parameter of the diffusion process representing the diffusive volatility. • See Appendix A
Λ	• Constant parameter of the compound jump process representing the average number of jumps per annum (year). • See Appendix A
A	• Constant parameter of the compound jump process representing the average jump size. • See Appendix A
γ	• Constant parameter of the compound jump process representing the standard deviation of the jump size α. • See Appendix A
Total Variance	• Total return variance for stock i in year t, based on daily stock returns. • Stock return data is obtained from CRSP.
Jump ($V_{i,t}^{j}$)	• The jump component of total return variance for stock i in year t, based on daily stock return data.
Diffusion ($V_{i,t}^{d}$)	• The diffusive component of total return variance for stock i in year t, based on daily stock return data.
Bid-Ask Spread (Liq)	• Annual average bid-ask spread for firm i across all intraday quotes based on available TAQ data.
PIN	• The probability of informed trade as measured by Brown and Hillegeist (2007). • Annual data are obtained from Stephen Brown's website.
Turnover	• The annual average ratio of daily volume to shares-outstanding for firm i in year t. • Daily data is obtained from CRSP.
Size	• Natural log of the market cap of the firm measured at the end of the calendar year, as reported by CRSP.
Forecaster	• An indicator variable that equals 1 if the firm issues at least one earnings forecast in three out of four quarters in a given year, and zero otherwise (Rogers et al. 2009). • Management forecast activity is obtained from First Call's Company Issued Guidelines (CIG) database.
Num_Forecasts	• Natural log of (1+ the number of management earnings forecasts issued in a given year).
Dispersion	• The dispersion of analyst forecasts scaled by the firms' price in the prior month. • Analyst forecast data is obtained from the IBES summary file. We use the first available observation in the calendar year.

	• Price is obtained from the CRSP monthly file
Market-to-Book (MTB)	• The market value of equity / the book value of equity at the beginning of year t (end of year t-1).* • The book and market value of equity is obtained from Compustat.
Leverage	• Ratio of (debt in current liabilities + long term debt) / (total assets) at the beginning of year t (end of year t-1).* • Data are obtained from Compustat.
Return on assets (ROA)	• Annual earnings before extraordinary items at the beginning of year t (end of year t-1) *, scaled by total assets. • Data are obtained from Compustat.
Loss	• An indicator variable equal to one if the firm's annual net income is negative at the beginning of year t (end of year t-1).* • Earnings data are obtained from Compustat.
Institutional Ownership	• The (%) of outstanding shares held by institutions based on quarter-end 13F filings, for the first quarter in the year • The variable is constructed by WRDS in its s34 database. • In cases where the (%) reported exceeds 100%, we redefine the variable to equal 100%.
Total Return	• Total returns in year t, as reported by CRSP in the monthly file. • Returns are measured for the entire calendar year.
Analysts Following	• Natural log of (1 + the number of annual earnings estimates (for the next fiscal period) present in the IBES summary file in year t. • We use the record at the end of the calendar year (November or December). • If no data are present on IBES, the variable is set to zero.
Earnings Volatility	• The standard deviation of annual operating income after depreciation scaled by total assets at the beginning of year t (end of year t-1) *, measured over five years, using a minimum of three years. • Data are obtained from Compustat.

* Compustat based variables are measured during the current year for firms with a fiscal year end between January and June. Compustat based variables are measured during the prior year for firms with a fiscal year end between June and December.

Table 1: Descriptive Statistics

This table reports descriptive statistics for our sample. Panels A reports average estimates for total, jump, and diffusive return variances as defined in Equations (4) and (5), multiplied by 100. Variance is calculated for each firm *i* in year *t* using daily stock return data. Panel B reports the corresponding volatilities (standard deviations). Total volatility is the realized standard deviation of daily returns. The diffusive and jump components reported in Panel B equal the square root of their model implied variances. Panel C reports descriptive statistics for the remaining variables employed in our analysis. We report summary statistics for the raw variables even though we employ log transformations for some of the variables in our regressions. The number of observations in our primary sample where we obtain estimates for jump and diffusive daily return variances is 55,558. See Appendix B for detailed variable definitions.

VARIABLES	Mean	p25	p50	p75	SD
Panel A: Daily Stock Return Variance (x100)					
Total	0.1096	0.0204	0.0591	0.1412	0.1381
Jump	0.0653	0.0081	0.0300	0.0821	0.0921
Diffusion	0.0443	0.0123	0.0291	0.0591	0.0460
Panel B: Daily Stock Return Volatility (Std)					
Total	0.0292	0.0169	0.0255	0.0376	0.0168
Jump	0.0203	0.0090	0.0173	0.0286	0.0159
Diffusion	0.0186	0.0111	0.0170	0.0243	0.0100

Panel C

VARIABLES	N	Mean	p25	p50	p75	SD
Bid-Ask Spread (%)	55,558	1.858	0.307	0.852	2.36	2.428
Analyst Following	55,558	4.5	0	2.0	7.0	5.97
Forecaster	46,451	0.195	0	0	0	0.396
Num_Forecasts	46,451	1.50	0	0	1.0	3.09
Dispersion	29,369	0.0139	0.0006	0.0016	0.0048	0.0624
MTB	45,808	2.77	1.13	1.79	3.00	3.38
Leverage	46,830	0.208	0.019	0.151	0.323	0.221
ROA	44,942	-0.020	-0.019	0.024	0.075	0.267
Earnings volatility	46,374	0.085	0.014	0.033	0.080	0.194
Loss	46,948	0.298	0	0	1.0	0.457
Institutional Ownership	48,577	0.475	0.158	0.474	0.775	0.326
Total Return	47,203	0.125	-0.203	0.069	0.341	0.540
Market Cap ($ Millions)	55,558	1,847	88.83	318.80	1,246	4,556
Turnover	55,558	1.589	0.402	0.921	1.901	9.254

Table 2: The Information Environment and Jump Volatility: Issuance of Management Forecasts

This table reports results for the estimation of Equation (4), which estimates the relation between the management forecasting policy of the firm and jump volatility. Forecaster is an indicator variable that equals 1 if the firm issues at least one earnings forecast in three out of four quarters in a given year, and zero otherwise (Rogers et al. 2009). We multiple the variables Jump, Diffusion, and Bid-Ask Spread by 100 for expositional purposes. Statistical significance levels are denoted by *** p<0.01, ** p<0.05, * p<0.1. *t-statistics* based on standard errors clustered at the firm level are reported in parentheses. See Appendix B for detailed variable definitions.

VARIABLES	Jump Variance ($V_{i,t}^{j}$)			
Forecaster	-0.0172***	-0.0151***	-0.0052***	-0.0043***
	[-10.30]	[-9.13]	[-3.24]	[-2.75]
Bid-Ask Spread		0.0134***	0.0082***	0.0079***
		[26.46]	[12.32]	[12.18]
Diffusion				0.2292***
				[10.48]
MTB			0.0010***	0.0009***
			[3.10]	[2.76]
Leverage			0.0000	0.0005
			[0.00]	[0.08]
ROA			-0.0080*	-0.0074
			[-1.69]	[-1.57]
Loss			0.0127***	0.0107***
			[7.62]	[6.57]
Institutional Ownership			-0.0081	-0.0067
			[-1.57]	[-1.34]
Total Return			0.0095***	0.0081***
			[6.95]	[6.00]
Size (ln)			-0.0405***	-0.0378***
			[-21.23]	[-21.04]
Analyst Following (ln)			0.0106***	0.0093***
			[6.82]	[6.20]
Earnings Volatility			0.0274***	0.0224***
			[3.44]	[3.02]
Observations	46,451	46,451	31,319	31,319
Adj. R-squared	0.545	0.577	0.620	0.626
Fixed Effects	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Table 3: The Information Environment and Jump Volatility: Number of Management Forecasts

This table reports results for the estimation of Equation (4), which estimates the relation between the management forecasting policy of the firm and jump volatility. Num_Forecasts equals the natural log of (1+ the number of management earnings forecasts issued in a given year). We multiple the variables Jump, Diffusion, and Bid-Ask Spread by 100 for expositional purposes. Statistical significance levels are denoted by *** p<0.01, ** p<0.05,* p<0.1. *t-statistics* based on standard errors clustered at the firm level are reported in parentheses. See Appendix B for detailed variable definitions.

VARIABLES	Jump Variance ($V_{i,t}^{j}$)			
Num_Forecasts	-0.0116***	-0.0100***	-0.0027***	-0.0022**
	[-10.44]	[-9.13]	[-2.59]	[-2.18]
Bid-Ask Spread		0.0133***	0.0082***	0.0079***
		[26.38]	[12.33]	[12.19]
Diffusion				0.2295***
				[10.49]
MTB			0.0010***	0.0009***
			[3.12]	[2.78]
Leverage			-0.0000	0.0005
			[-0.00]	[0.08]
ROA			-0.0079*	-0.0073
			[-1.67]	[-1.56]
Loss			0.0127***	0.0107***
			[7.59]	[6.55]
Institutional Ownership			-0.0082	-0.0068
			[-1.60]	[-1.35]
Total Return			0.0094***	0.0081***
			[6.92]	[5.98]
Size (ln)			-0.0405***	-0.0377***
			[-21.18]	[-20.98]
Analyst Following (ln)			0.0106***	0.0094***
			[6.84]	[6.22]
Earnings Volatility			0.0274***	0.0224***
			[3.44]	[3.02]
Observations	46,451	46,451	31,319	31,319
Adj. R-squared	0.546	0.578	0.620	0.626
Fixed Effects	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Table 4: The Information Environment and Jump Volatility: Analyst Forecast Dispersion

This table reports results for the estimation of Equation (4), which estimates the relation between analyst forecast dispersion and jump volatility. Dispersion equals the dispersion of analyst forecasts scaled by the firms' price in the prior month. We multiple the variables Jump, Diffusion, and Bid-Ask Spread by 100 for expositional purposes. Statistical significance levels are denoted by *** p<0.01, ** p<0.05, * p<0.1. *t-statistics* based on standard errors clustered at the firm level are reported in parentheses. See Appendix B for detailed variable definitions.

VARIABLES	Jump Variance ($V_{i,t}^{j}$)			
Dispersion	0.3483***	0.3058***	0.2764***	0.2501***
	[14.70]	[13.24]	[6.86]	[6.42]
Bid-Ask Spread		0.0173***	0.0083***	0.0085***
		[13.78]	[6.54]	[6.95]
Diffusion				0.2368***
				[8.90]
MTB			0.0009***	0.0007**
			[2.94]	[2.55]
Leverage			0.0024	0.0023
			[0.38]	[0.38]
ROA			-0.0144**	-0.0139**
			[-2.50]	[-2.46]
Loss			0.0112***	0.0090***
			[6.26]	[5.22]
Institutional Ownership			-0.0185***	-0.0173***
			[-3.88]	[-3.71]
Total Return			-0.0016	-0.0026*
			[-1.09]	[-1.75]
Size (ln)			-0.0273***	-0.0250***
			[-15.14]	[-14.63]
Analyst Following (ln)			0.0052***	0.0046***
			[3.14]	[2.84]
Earnings Volatility			0.0427***	0.0329***
			[4.09]	[3.23]
Observations	29,369	29,369	24,677	24,677
Adj. R-squared	0.538	0.555	0.587	0.594
Fixed Effects	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Table 5: The Information Environment and Jump Volatility: Brokerage House Closures

This table reports results for the estimation of Equation (5), which estimates the effect of an exogenous reduction in analyst coverage on jump volatility. We measure the exogenous reduction in analyst coverage using brokerage house closures. Panel A reports results for all available observations as discussed in Section 3.1. Panel B reports results only for firms that experience a closure at some point in our sample. Treat is an indicator variable equal to one for firms that experience a brokerage house closure, and zero otherwise. Post is an indictor variable equal to one for firm-years including and following the year of the brokerage house closure, and zero otherwise. Treat*Post is the interaction of Treat and Post. The main effects, Treat and Post, are subsumed by the firm and year fixed effects. Columns 1–3 employ Jump as the dependent variable. Columns 4–5 employ diffusion as the dependent variable and serve as a counterfactual test. We multiple the variables Jump, Diffusion, and Bid-Ask Spread by 100 for expositional purposes. Statistical significance levels are denoted by *** p<0.01, ** p<0.05, * p<0.1. *t-statistics* based on standard errors clustered at the firm level are reported in parentheses. See Appendix B for detailed variable definitions.

Panel A

VARIABLES	Jump Variance ($V_{i,t}^{j}$)			Diffusion Variance ($V_{i,t}^{d}$)	
	(1)	(2)	(3)	(4)	(5)
Treat * Post	0.0041***	0.0047***	0.0046***	0.0003	0.0004
	[2.87]	[3.31]	[3.34]	[0.36]	[0.56]
Diffusion			0.2899***		
			[12.48]		
Bid-Ask Spread		0.0090***	0.0083***		0.0023***
		[13.83]	[12.99]		[7.10]
Size (ln)	-0.0381***	-0.0309***	-0.0282***	-0.0113***	-0.0095***
	[-26.30]	[-21.03]	[-20.63]	[-16.08]	[-13.39]
Analyst Following (ln)	0.0035**	0.0060***	0.0056***	0.0009	0.0016**
	[2.57]	[4.44]	[4.26]	[1.20]	[2.01]
Observations	35,531	35,531	35,531	35,531	35,531
Adj. R-squared	0.593	0.605	0.614	0.547	0.550
Fixed Effects	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Panel B

VARIABLES	Jump Variance ($V_{i,t}^{j}$)			Diffusion Variance ($V_{i,t}^{d}$)	
	(1)	(2)	(3)	(4)	(5)
Treat * Post	0.0033**	0.0032**	0.0031**	0.0001	0.0002
	[2.30]	[2.22]	[2.27]	[0.19]	[0.20]
Diffusion			0.3300***		
			[8.99]		
Bid-Ask Spread		0.0092***	0.0093***		-0.0003
		[4.83]	[4.97]		[-0.35]
Size (ln)	-0.0328***	-0.0296***	-0.0263***	-0.0099***	-0.0101***
	[-15.57]	[-14.27]	[-13.89]	[-9.67]	[-9.64]
Analyst Following (ln)	0.0065***	0.0093***	0.0087***	0.0019	0.0018
	[2.95]	[4.20]	[4.17]	[1.52]	[1.43]
Observations	13,012	13,012	13,012	13,012	13,012
Adj. R-squared	0.646	0.629	0.633	0.646	0.620
Fixed Effects	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Table 6: Volatility Structure and Liquidity: Univariate Portfolio Analysis

We sort all stocks, in each year, on one volatility component, and then resort the stocks in each quintile on the other component. In Panel A, we first sort stocks on diffusive volatility and form portfolios *d*=1,...,5. Then, each diffusive portfolio *d* is sorted again using the jump volatility component, to form five additional portfolios. This allows us to test the marginal effect of an increase in total volatility which is driven solely by jump volatility, controlling for the diffusive component. In Panel B, we first sort stocks on jump volatility and then on diffusive volatility to test the marginal effect of diffusive volatility while controlling for jump volatility. We report average bid-ask spreads in period *t+1* for each portfolio. We also report the differences in bid-ask spreads between the highest and lowest portfolios and their related *t-statistics*.

Portfolio	Low	2	3	4	High
Panel A: Controlling for Diffusive Volatility					
Low Jump	0.0162	0.0085	0.0097	0.0090	0.0115
2	0.0149	0.0090	0.0090	0.0099	0.0160
3	0.0147	0.0103	0.0103	0.0125	0.0208
4	0.0183	0.0157	0.0151	0.0169	0.0284
High Jump	0.0339	0.0266	0.0261	0.0285	0.0393
High-Low	*0.0176*	*0.0181*	*0.0164*	*0.0194*	*0.0278*
t-stat	*18.94*	*22.90*	*20.86*	*24.80*	*27.57*
Panel B: Controlling for Jump Volatility					
Low Diffusion	0.0166	0.0169	0.0204	0.0253	0.0364
2	0.0141	0.0106	0.0133	0.0190	0.0270
3	0.0086	0.0088	0.0113	0.0166	0.0262
4	0.0092	0.0089	0.0102	0.0139	0.0294
High Diffusion	0.0093	0.0102	0.0139	0.0184	0.0361
High-Low	*-0.0073*	*-0.0067*	*-0.0065*	*-0.0068*	*-0.0003*
t-stat	*-13.10*	*-10.95*	*-8.42*	*-7.76*	*-0.20*

Table 7: Volatility Structure and Liquidity, Fama-Macbeth Regressions

This table reports results for the Fama-MacBeth regressions of total volatility and bid-ask spread, as well as the marginal effects of each volatility component on bid-ask spreads, as specified in Equations (6) & (7). The first column corresponds to Equation (6) and estimates the effect of total volatility on bid-ask spreads. The second column corresponds to Equation (7) and estimates the effect of each volatility component on bid-ask spreads separately. Model A and B are additional versions of Equation (7) as discussed in Section 4.2.4. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1, and *t-statistics* are reported in parentheses. See Appendix B for detailed variable definitions.

VARIABLES	Bid-Ask Spread			
	Total Volatility	Volatility Components	Model A	Model B
Diffusion		-1.8707***		-6.1256***
		[-4.14]		[-9.25]
Jump		4.2549***	6.1256***	
		[7.84]	[9.25]	
Total Variance	2.1974***		-1.8707***	4.2549***
	[5.52]		[-4.14]	[7.84]
Size (ln)	-0.0082***	-0.0081***	-0.0081***	-0.0081***
	[-10.09]	[-9.86]	[-9.86]	[-9.86]
Constant	0.1209***	0.1196***	0.1196***	0.1196***
	[10.90]	[10.70]	[10.70]	[10.70]
Observations	44,171	44,171	44,171	44,171
Avg. R-squared	0.483	0.489	0.489	0.489

Table 8: Volatility Structure and Liquidity, Controlling for Information Asymmetry

This table reports results for Equation (7) related to the relation between volatility and illiquidity while controlling for information asymmetry. 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. PIN related data are obtained from Stephen Brown's website and are based on Brown and Hillegeist (2007). The results in the first column are based on all firm years in our sample. Columns 2-6 report results for each information asymmetry quintile separately, sorted from low to high. Statistical significance levels are denoted by *** p<0.01, ** p<0.05, * p<0.1, and *t-statistics* are reported in parentheses. See Appendix B for detailed variable definitions.

VARIABLES	Bid-Ask Spread					
	All	Low	Rank 2	Rank 3	Rank 4	High
Jump	4.3676***	6.6467***	3.3863***	2.3236***	3.0447***	6.3039***
	[5.91]	[4.16]	[4.42]	[5.58]	[7.11]	[5.96]
Diffusion	-0.7488	0.5934	-1.0056	-0.6360	-1.2862**	3.8679
	[-0.80]	[0.58]	[-1.22]	[-0.69]	[-2.42]	[1.71]
Size (ln)	-0.0071***	-0.0076***	-0.0051***	-0.0047***	-0.0046***	-0.0102***
	[-10.91]	[-12.65]	[-12.75]	[-10.06]	[-13.79]	[-8.58]
PIN	0.0231***					
	[10.35]					
Constant	0.0930***	0.1120***	0.0758***	0.0712***	0.0707***	0.1498***
	[10.65]	[12.23]	[12.73]	[10.43]	[14.41]	[8.93]
Observations	38,355	7,675	7,672	7,670	7,672	7,666
Avg. R-squared	0.524	0.523	0.477	0.455	0.467	0.496

Table 9: Volatility Structure and Liquidity, Predicted Exogenous Jumps

This table reports results for the 2nd stage of the two-stage shock based Instrumental Variable (IV) design discussed in Section 4.6. To provide more causal evidence, we employ the predicted values of the jump volatility component based on exogenous reductions in analyst coverage driven by brokerage house closures as estimated in Table (5), as an instrument for Jump. We apply a two-stage regression procedure. In the first stage, we use the regression depicted in Column (3) of Table (5), excluding the bid-ask spread variable, to derive predicted values for jumps. In the second stage, we use Equation (8) to estimate the effect of the two volatility components on bid-ask spreads. Since our predicted jump component captures only exogenous values not driven by spreads, we are able to test for causal effects from jumps to spreads. Statistical significance levels are denoted by *** p<0.01, ** p<0.05, * p<0.1, and *t-statistics* are reported in parentheses. See Appendix B for detailed variable definitions.

Variables	Bid-Ask Spread
Jump Hat	40.8231***
	[3.59]
Diffusion	-11.6865**
	[-3.25]
Size (ln)	0.7402**
	[2.48]
Analyst Following (ln)	-0.3184***
	[-6.77]
Constant	-9.8987*
	[-2.21]
Observations	27,932
R-squared	0.484

Table 10. Volatility Structure and Liquidity, Controlling for Turnover

This table uses a portfolio analysis approach to test for the causal effects of jumps on liquidity by increasing the jump volatility component while controlling for turnover. By construction, stocks with high turnover ratios do not exhibit thin trading. We first sort all stocks in each year based on their turnover ratio into five different portfolios, from low to high. Then, for each turnover portfolio, we double sort on total volatility and jump-driven volatility creating 25 portfolios for each turnover level. To control for total volatility, we calculate average bid-ask spreads per jump level across all five total volatility buckets. Therefore, we have a five-by-five portfolio ranking sorted on turnover level and jump-driven volatility level while controlling for total volatility. We report average bid-ask spreads in period *t+1* for each portfolio, and differences in bid-ask spreads between the highest and lowest portfolios and their related *t-statistics*. See Section 4.2.7 for more detailed description.

Jump	Low	2	3	4	High	*High-Low*	*t-stat*
Low Turnover	0.0354	0.0384	0.0389	0.0424	0.0479	*0.0125*	*10.73*
2	0.0174	0.0201	0.0213	0.0227	0.0248	*0.0074*	*10.08*
3	0.0083	0.0103	0.0107	0.0126	0.0151	*0.0068*	*13.19*
4	0.0050	0.0058	0.0059	0.0071	0.0088	*0.0038*	*10.76*
High Turnover	0.0040	0.0044	0.0044	0.0052	0.0066	*0.0026*	*8.26*

Table 11. Volatility Structure and Liquidity, Controlling for Turnover

This table reports results for the Fama-MacBeth regressions of total volatility and bid-ask spread, as well as the marginal effects of each volatility component on bid-ask spreads after controlling for turnover. The first column corresponds to Equation (6) and the second column corresponds to Equation (7). Statistical significance levels are denoted by *** p<0.01, ** p<0.05, * p<0.1, and *t-statistics* are reported in parentheses. See Appendix B for detailed variable definitions

VARIABLES	Bid-Ask Spread	
Jump		5.1547***
		[8.30]
Diffusion		0.0225
		[0.04]
Total Variance	3.4453***	
	[6.02]	
Size (ln)	-0.0076***	-0.0075***
	[-11.93]	[-11.55]
Turnover	-0.0016***	-0.0015***
	[-5.50]	[-5.44]
Constant	0.1145***	0.1136***
	[12.90]	[12.57]
Observations	44,171	44,171
Avg. R-squared	0.505	0.509