Asymmetric Information and the Distribution of Trading Volume *

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Abstract

We propose the Volume Coefficient of Variation (VCV), the ratio of the standard deviation to the mean of trading volume, as a new and easily computable measure of information asymmetry in security markets. We use a microstructure model to demonstrate that VCV is strictly increasing in the proportion of informed trade. Empirically, we find that firm-year observations of VCV, computed from daily trading volumes, are correlated with extant firm-level measures of asymmetric information in the cross-section of US stocks. Moreover, VCV increases following exogenous reductions in analyst coverage induced by brokerage closures, and steeply decreases around earnings announcements.

Keywords: VCV, Trading volume, Informed trading.
JEL classification: D82, G12, G14

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1 Introduction

In this paper, we analyze the distribution of trading volume in security markets, and investigate how it depends on the proportion of informed trade. We consider a market where liquidity seekers submit orders to competitive liquidity providers (market makers), who absorb the order imbalance and set the clearing price, as in Kyle (1985). Liquidity seekers are either informed or uninformed. Uninformed liquidity seekers place uncorrelated orders, while informed orders are highly correlated. Uninformed orders are therefore mostly matched to each other, while informed orders generate order imbalances that need to be absorbed by market makers. We derive simple expressions for the first two moments of the distribution of total trading volume as functions of the proportion of informed trade. Specifically, we show that the coefficient of variation (the ratio of the standard deviation to the mean) of trading volume increases monotonically in the proportion of informed trade. We propose the volume coefficient of variation (VCV) as a novel measure of the proportion of information trade. VCV is easy to compute and requires only observations of trading volume, as opposed to quotes, prices, or signed order flow.

The intuition behind our measure is that the distribution of trading volume depends on the correlation of individual orders. If all liquidity seekers are uninformed and place uncorrelated orders, their orders are mostly netted out against each other, and net order flow is relatively low compared to observed trading volume. In this case, trading volume follows a slightly skewed Normal-like distribution. As more market participants are informed, liquidity demand becomes more correlated, so that the expected net order flow takes up a higher share of total trading volume, resulting in a more dispersed and skewed distribution of trading volume. We show that the coefficient of variation adequately captures the mapping from the proportion of informed and hence correlated trade to the volume distribution. In addition to the analytical results, we conduct an extensive simulation exercise and provide empirical evidence in support of our main result: VCV increases in the proportion of informed trade.[1]

Adverse selection and asymmetric information in security markets have been widely studied since Bagehot (1971) identified it as the key determinant of market illiquidity. Copeland and Galai (1983), Kyle (1985, 1989), Glosten and Milgrom (1985), Karpoff (1986), Easley and O'Hara (1992), Admati and Pfleider (1989), Foster and Viswanathan (1994), and many others, have increased our understanding of the strategic behavior of asymmetrically informed traders and their effect on security markets. There has been no shortage of subsequent papers that aim to measure information asymmetries in security markets.

Easley et al. (1996) develop a measure for the probability of informed trading, the well-known PIN measure. They use the model of Glosten and Milgrom (1985) to estimate the proportion of informed traders from the dynamics of the signed order process. The PIN measure has been widely used to study information asymmetries in security markets.[2] Both PIN and VCV are expected to increase in the order imbalance generated by correlated informed demand. The PIN measure is estimated from transaction-level data and requires trades to be classified as either buy- or sell-initiated. Also other information asymmetry measures, such as order flow volatility (Chordia et al., 2017) and XPIN (Bongaerts et al., 2016), rely on signed transaction-level data. It has been recognized that such order classification, e.g. using the Lee and Ready (1991) algorithm, is not error-free and has become increasingly problematic due to high-frequency trading (e.g. Boehmer et al., 2007; Easley et al., 2012; Johnson and So, 2018). Computing VCV does not require signed transaction-level data. Instead, VCV is estimated from volume data only.

[1]To the best of our knowledge, we are the first to relate the coefficient of variation of trading volume to asymmetric information. Chordia et al. (2001) use the coefficient of variation of trading volume when examining the relation between stock returns and the variability of trading volume, without relating this measure to asymmetric information.

[2]Easley et al. (1997a and 1997b) analyze the information content around trade lags and trade size. Applications of PIN include, among others, the pricing of information asymmetry (Easley et al., 2002), the impact of analyst coverage on informational content (Easley et al., 1998), stock splits (Easley et al., 2001), dealer vs. auction markets (Heidle and Huang, 2002), trader anonymity (Gramming et al., 2001), information disclosure (Vega, 2006; Brown and Hillegeist, 2007), corporate investments and M&A (Chen et al., 2007; Aktas et al., 2007), ownership structure (Brockman and Yan, 2009), and the January effect (Kang, 2010).

Duarte and Young (2009) argue that (unadjusted) PIN is not only measuring informed trade, but also general illiquidity unrelated to information asymmetry.[3] They derive a new measure of general illiquidity unrelated to informed trading: PSOS (Probability of Systematic Order-flow Shock), as well as a measure called *Adjusted* PIN, which measures asymmetric information, net of unrelated illiquidity effects. We compare VCV to various PIN measures and find that VCV is strongly related to PIN, but even more so to Adjusted PIN, while the relationship to PSOS is weak. This corroborates that VCV is a measure of informed trading, rather than general illiquidity.

Llorente et al. (2002) propose the C2-measure that captures the relation between daily trading volume and return persistence, as a proxy for information asymmetry. C2 deduces the proportion of informed trade from the premise that returns generated by informed trade are likely to be persistent, while uninformed trade leads to return reversals. In a recent paper, Johnson and So (2018) propose the multimarket information asymmetry (MIA) measure, which is based on the relative daily trading volumes in options and stocks, following the premise that informed investors are more likely than uninformed investors to trade in options. Although MIA, like VCV, is a simple measure to compute, it requires access to option trading volume in addition to equity trading volume. We find that our VCV measure is positively correlated with both the MIA measure of Johnson and So (2018) and the C2 measure of Llorente et al. (2002).

Recent studies find that institutional ownership is associated with improved disclosure of information (Boone and White, 2015) and more informative market prices (Bai et al., 2016). Consistent with these results, we find from 13F filings that firms with more institutional shareholders (i.e. high breadth of ownership) have on average lower VCVs. We also look specifically at two types of institutional investors that can be considered rela-

[3]Other papers in the debate on the validity of PIN include Easley et al. (2010), Akay et al. (2012), and Duarte et al. (2017). Other studies focus on the estimation robustness, particularly in high-turnover stocks (Lin and Ke, 2011; Yan and Zhang, 2012). In response to these latter critiques, and the advent of high frequency trading, Easley et al. (2012) develop the volume synchronized PIN, or VPIN. This estimator captures not only information asymmetry but also order flow toxicity, i.e.: the risk of unbalanced orderflows.

tively informed about a firm: *monitoring* investors, defined as those institutional investors for which the firm represents a significant allocation of funds in the institution's portfolio (Fich et al., 2015), and *dedicated* investors, defined as institutional investors that predominantly make long-term investments in a selective set of stocks (Bushee and Noe, 2000; Bushee, 2001). We find that, controlling for breadth of ownership, VCV is higher for firms with monitoring and/or dedicated (i.e. informed) investors.

The crux of our theoretical analysis in Section 2 is a Kyle (1985) model with informed and uninformed liquidity seekers and price-setting market makers. Instead of focusing on prices and orderflows, we analyze the total trading volume. We introduce a simple expression for the observed total trading volume, and derive the first and second moments as a function of the number of market participants, their trading intensity, and the proportion of informed trade. We demonstrate that both the expected value and the standard deviation of volume increase linearly in the proportion of informed trade, but that the standard deviation does so at a higher rate. The coefficient of variation of trading volume is therefore a natural measure of the proportion of informed trade, as VCV increases monotonically in the proportion of informed trade, while it is asymptotically independent of the number of market participants and of their trading intensity.

We recognize that the proportion of informed trade is endogenous and depends on the number of informed traders, the strength of their informational advantage, and the trading activity of the uninformed traders, as in Kyle (1985) and follow up papers.[4] In this paper, we are agnostic about the strategic motives, preferences or time horizons of the informed traders, and are only interested in the resulting proportion of liquidity seeking demand originating from these informed market participants. Our analytical expression of VCV in terms of the proportion of informed trade holds regardless of the mechanism by which the proportion of informed trading is determined. To illustrate this, we con-

[4]Strategic behaviour of informed traders is also considered by Admati and Pfleiderer (1988), Subrahmanyam (1991), Holden and Subrahmanyam (1992), and Foster and Viswanathan (1996), among others. Collin-Dufresne and Fos (2015) provide empirical evidence of such strategic timing by informed investors.

sider a model in which the informed traders choose their demand strategically, so that the proportion of informed trade is endogenously determined in equilibrium, and find an equivalent relation between VCV and the *equilibrium* proportion of informed trade. We also demonstrate that VCV is distinct from Kyle's lambda. The relation between lambda and the proportion of informed trade is weak and not monotonic. The reason is that when the number of informed traders increases, they reduce the aggressiveness of their trading, thereby mitigating price impact. Also in our empirical analysis, we find that VCV is distinct from measures of price impact, such as Amihud (2002) illiquidity.

To further analyze the relation between informed trading and the distribution of total trading volume, and to gain insight into the small sample properties of VCV, we conduct a Monte Carlo analysis in Section 3. We start by simulating our benchmark model and find, as predicted, that the generated volume distribution changes markedly as a function of the proportion of informed trade. Our simulations confirm that VCV strictly increases in the proportion of informed trade, even when the sample size or the number of market participants is low.

For our empirical analysis in Section 4, we compute annual firm-level observations of VCV from daily volumes of all NYSE, AMEX and NASDAQ stocks from 1980 until 2016, obtained from CRSP. We use three distinct volume measures: *(i)* trading volume in dollars, *(ii)* turnover, and *(iii)* volume market shares (dollar-volume as a fraction of total market dollar-volume). These three measures of VCV turn out to be virtually identical, implying that VCV is not sensitive to aggregate market-level variation in trading volume. This is important, since it is well known that other factors besides idiosyncratic firm-level information can drive variation in trading activity, such as sentiment (Kumar and Lee, 2006), or common liquidity shocks (Admati and Pfleiderer, 1988; Brogaard et al., 2018).

Our cross-sectional analysis shows that VCV correlates, as expected, with various firm-level characteristics: firms that are smaller and younger have higher VCVs, as do stocks that see lower turnover, higher return volatility, and wider bid-ask spreads. In addition, VCV is significantly correlated with other indicators of asymmetric information, in particular with Adjusted PIN (Duarte and Young, 2009), and with patterns in institutional ownership. As further evidence of VCV measuring informed trading, we show that, controlling for Amihud (2002) illiquidity, return reversals are weaker for high-VCV stocks, consistent with informed trading being predictive of future price changes.

Section 5 documents time-series patterns of VCV around information events. First, we exploit exogenous terminations in analyst coverage due to brokerage closures, similar to Kelly and Ljungqvist (2012), Derrien and Kecskes (2013), and Chen and Lin (2017). We find that the VCV of affected firms significantly increases in the year following such disruptions to the information environment. We expect the impact of coverage terminations to be more severe for firms that already have low analyst coverage prior to the brokerage closure. Our results confirm this hypothesis: the increase in VCV following closure-induced coverage terminations is much larger for stocks with low analyst coverage.

Finally, we analyze the cross-sectional VCV computed from the cross section of trading volumes around earnings announcements. It has been widely recognized that information asymmetries are resolved around these events. We expect that the proportion of informed trade is high close to earnings announcements, as information asymmetries build up and discourage uninformed traders to trade just before such events (See Milgrom and Stokey, 1982; Black, 1986; Wang, 1994; and Chae, 2005). After the announcement, the playing field is levelled and the market is more attractive for uninformed traders. Our empirical investigations bear this out. From a comprehensive sample of over 300,000 quarterly earnings announcements of U.S. firms, we find VCV to be relatively high prior to announcements, while VCV is significantly lower in the days following the announcement.

2 Theory

To analyze the distribution of trading volume, we first present a simple model in which we postulate M individual liquidity seekers, who each submit Normally distributed orders with mean zero and standard deviation σ, and where competitive liquidity providers (market makers) absorb the net order flow. Proportion η of the M liquidity seekers is informed, with ηM being an integer. We refer to σ as *trading intensity*. The assumption that informed and uninformed traders have equal trading intensity is for convenience only and without loss of generality: the trading volume distribution would be identical if the there were be $k\eta M$ informed traders who each trade with intensity $\frac{\sigma}{k}$. For now, we assume η to be exogenous. In the next subsection, we endogenize η by allowing informed investors to choose their trading intensity strategically.

We denote the individual demands of all (informed and uninformed) liquidity seekers y_i, for which positive values indicate buy orders and negative values indicate sell orders. The order imbalance (net order flow) is the sum of all orders, $\sum_M y_i$, which is taken up by the liquidity providers who determine the price. This imbalance is typically not publicly observable. Total trading volume can then be written as:

$$V = \tfrac{1}{2}\left(\sum_M |y_i| + \left|\sum_M y_i\right|\right). \tag{1}$$

The term inside brackets is the "double-counted transaction volume", counting both buys and sells, of (*i*) the liquidity seekers (the first term) and (*ii*) the liquidity providers (the second term). This double-counted volume includes the trades among liquidity seekers, as well as the trades between the liquidity providers and unmatched liquidity seekers.[5]

As an example, consider five liquidity seekers whose demands are -1, 2, 2, -2, 1. The net order flow is two, which means that the liquidity providers end up selling two units.

[5]This expression for trading volume is similar to that in Admati and Pfleiderer (1988) and Grundy and McNichols (1989).

The observed trading volume is five: we have three units sold by liquidity seekers, five units bought by liquidity seekers and two units sold by liquidity providers. The double-counted volume is thus ten, and the commonly recorded single-counted volume is half this number.

The orders of the informed liquidity seekers are perfectly correlated, so that all ηM informed traders submit identical orders. On the other hand, the demands of the $(1-\eta)M$ uninformed liquidity seekers are uncorrelated (*i.i.d.*). Following these assumptions, the net order flow follows a Normal distribution around zero, as in Kyle (1985):

$$\sum_{M} y_i \sim N\left(0, \sigma^2\left(\eta^2 M^2 + (1-\eta)M\right)\right). \tag{2}$$

The variance of the net order flow is a nonlinear function of η, due to the different correlations of informed and uninformed demand. When most liquidity seekers are uninformed, their orders will be mostly matched to each other and net order flow is low. When most traders are informed, their correlated demands can lead to large imbalances. As a result, the standard deviation of the unobservable net order flow is increasing in the proportion of informed trade η.

We now derive the first two moments of the observable total trading volume (Eq.1) as a function of η. Using the properties of the Half Normal distribution we find:[6]

$$\begin{aligned} E[V] &= \tfrac{1}{2}\left(E\left[\textstyle\sum_M |y_i|\right] + E\left[\left|\textstyle\sum_M y_i\right|\right]\right) \\ &= \tfrac{\sigma M}{\sqrt{2\pi}}\left(1+\sqrt{\eta^2+(1-\eta)M^{-1}}\right). \end{aligned} \tag{3}$$

From this we see that as the number of market participants M increases, expected trading volume per capita converges to a linear increasing function of the proportion of informed trade η:

$$\lim_{M\to\infty} E\left[\frac{V}{M}\right] = \frac{\sigma}{\sqrt{2\pi}}\left(1+\eta\right). \tag{4}$$

[6]If $x \sim N\left(0,\sigma^2\right)$, then $|x|$ follows a *Half Normal* distribution with $E\left(|x|\right) = \frac{\sigma\sqrt{2}}{\sqrt{\pi}}$ and $Var\left(|x|\right) = \sigma^2\left(1-\frac{2}{\pi}\right)$.

To analyze the variance of the observed trading volume, we consider each of the three components of the double-counted volume that can be attributed to *(i)* informed liquidity seekers $\left(\sum_{1\dots\eta M}|y_i|\right)$, *(ii)* uninformed liquidity seekers $\left(\sum_{\eta M+1\dots M}|y_i|\right)$, and *(iii)* liquidity providers ($|\sum_M y_i|$). The variances and covariances of these three components are derived in Appendix A. For large M, we find that the variance of of the per capita trading volume increases in η^2:

$$\lim_{M\to\infty} Var\left(\frac{V}{M}\right) = \sigma^2\left(1-\frac{2}{\pi}\right)\eta^2. \tag{5}$$

We thus see that for large M, the ratio of the standard deviation to the mean (the coefficient of variation) of trading volume is strictly increasing in η and is independent of the number of market participants M and their trading intensity σ.

<u>Proposition 1</u>

Consider a market where M liquidity seeking traders submit Normally distributed market orders with mean zero and standard deviation σ, and where the net order flow is absorbed by liquidity suppliers. If ηM of the M liquidity seeking traders are informed:

i. *The coefficient of variation of observed trading volume increases monotonically in the proportion of informed traders, η.*

ii. *For large M, the relationship converges to:*

$$\lim_{M\to\infty}\frac{\sigma_V}{\mu_V} = \sqrt{2\pi-4}\frac{\eta}{\eta+1}, \tag{6}$$

where μ_V and σ_V denote the expected value and standard deviation of trading volume V.

Corollary

If $\hat{\mu}_V$ and $\hat{\sigma}_V$ denote the sample average and standard deviation of a sample of trading volumes generated by trading sessions with parameters $\{\sigma, M, \eta\}$,

$$VCV \equiv \frac{\hat{\sigma}_V}{\hat{\mu}_V} \tag{7}$$

is a consistent estimator of $\frac{\sigma_V}{\mu_V}$.

The Volume Coefficient of Variation (VCV) is a measure of informed trade. $E[VCV]$ increases monotonically in η.

Our finding that VCV is independent of σ and M is important. It means that even when σ and M are subject to exogenous variation, e.g. due to sentiment (Kumar and Lee, 2006), or correlated liquidity shocks (Admati and Pfleiderer, 1988; Brogaard et al., 2018), VCV will increase in the proportion of informed trade. We present simulations and empirical analyses in the next sections that strongly support this result.

The above analysis also shows that a direct estimator of the proportion of informed trade is implied from Eq.(6):

$$\hat{\eta} \equiv \frac{\hat{\sigma}_V}{\hat{\mu}_V \sqrt{2\pi - 4} - \hat{\sigma}_V}. \tag{8}$$

However, as our simulation results in Section 3 show, $\hat{\eta}$ is a consistent estimator of η only when demand is Normally distributed, M is large, and η is constant across observations. We find that $\hat{\eta}$ behaves particularly poorly in small samples or when we relax the assumptions of the model, primarily because its denominator can be close to zero or turn negative. On the other hand, We find that VCV is monotonically increasing in η under general conditions, including non-Normality and time-varying proportions of informed trade. For this reason, we propose VCV, as opposed to $\hat{\eta}$, as our measure of informed trade.

2.1 VCV in equilibrium

In this subsection, we demonstrate that the insights from our simple model also hold in a setting where the proportion of informed trade is endogenously determined, as in Kyle (1985). We now consider a model where multiple informed investors, with correlated noisy signals, choose their orders strategically while taking into account the strategies of the other informed investors.

In particular, we assume that there are m informed liquidity seekers, n uninformed liquidity seekers, and competitive liquidity providers whose number is sufficient to be competitive. We assume a zero interest rate and risk neutrality of all market participants. The informed traders place orders, denoted by x_j, after receiving a signal s_j equal to the liquidation value (v) plus an independent noise term: $s_j = v + \varepsilon_j$. The orders of the uninformed, denoted u_i, are *i.i.d.*, Normally distributed with mean zero and standard deviation σ_u. Due to risk neutrality and zero-interest, the expected liquidation value $E[v]$ equals the previous clearing price, p_0.

The $n + m$ individual liquidity seekers submit orders to the market where buy orders are matched to sell orders and the net orderflow $\sum_n u_i + \sum_m x_j$, is taken up by liquidity providers who set the price. Our model is thus a modified Kyle (1985) model, in which multiple imperfectly informed insiders compete. Similar models have been analyzed by Holden and Subrahmaniam (1992), Foster and Viswanathan (1994, 1996) and others.

We use the terminology and symbols of Kyle (1985), and look for the linear equilibrium in which the informed traders choose their trade as a linear function of their signal and the last traded price p_0:

$$x_j = \beta_j(s_j - p_0), \tag{9}$$

and the competitive market makers use the following linear pricing function:

$$p = p_0 + \lambda \left(\sum_n u_i + \sum_m x_j \right). \tag{10}$$

In equilibrium β_j and λ are determined jointly: the βs follow from the profit optimization problem of the informed traders, who take λ, s_j, p_0, and the other parameters $(n, m, \sigma_u, \sigma_v, \sigma_\varepsilon)$ as given, and (Kyle's) λ is determined by the liquidity providers who set the price at the expected value given the observed orderflow and knowledge on the trading aggressiveness of the informed investors (i.e. the βs).

The m profit maximizing informed investors each solve:

$$\max_{x_j} x_j (E[v|s_j] - p_0 - \lambda(x_j + E[\sum_n u_i + \sum_{m-1} x_{-j}|s_j]), \tag{11}$$

where x_{-j} denotes the orders of the informed traders other than j. The first order condition is $x_j^*(s_j) = \frac{s_j - p_0}{2\lambda} - \frac{m-1}{2} E[x_{-j}|s_j]$. Since the signal's noise component ε_j are *i.i.d.*, the final term, $E[x_{-j}|s_j]$, equals $\beta_{-j}(s_j - p_0)$, where β_{-j} is the trading aggressiveness for all traders except j. Hence, all traders set their demand following $x_j^*(s_j) = (s_j - p_0)\left(\frac{1}{2\lambda} - \frac{m-1}{2}\beta_{-j}\right)$, so that in equilibrium we have $\beta_j = \beta_{-j} = \beta = \frac{1}{\lambda(m+1)}$.

Simultaneously, the market makers set the equilibrium price at the expected value of v, conditional on the net orderflow $\sum_n u_i + \sum_m x_j$. From the projection theorem, we know that $E[v| \sum_n u_i, \sum_m x_j; p_0, \beta, \sigma_v, \sigma_u, n, m] = p_0 + \frac{m\beta\left(\sigma_v^2 + \sigma_\varepsilon^2\right)}{n\sigma_u^2 + m^2\beta^2(\sigma_v^2+\sigma_\varepsilon^2)} \left(\sum_n u_i + \sum_m x_j\right)$, implying that $\lambda = \frac{m\beta\left(\sigma_v^2 + \sigma_\varepsilon^2\right)}{n\sigma_u^2 + m^2\beta^2(\sigma_v^2+\sigma_\varepsilon^2)}$. Combining these two results, we find that in equilibrium:

$$\beta = \frac{\sqrt{n}\sigma_u}{\sqrt{m\left(\sigma_v^2 + \sigma_\varepsilon^2\right)}}; \qquad \lambda = \frac{\sqrt{m\left(\sigma_v^2 + \sigma_\varepsilon^2\right)}}{(m+1)\sqrt{n}\sigma_u}. \tag{12}$$

We now express trading volume as a function of the model's parameters. We first observe that total trading volume can now be written, similar to Eq.(1), as:

$$V = \frac{1}{2}\left(\sum_n |u_i| + \sum_m |x_j| + \left|\sum_n u_i + \sum_m x_j\right|\right). \tag{13}$$

The demands u_i and x_j both follow a Normal distribution around zero. We find from (9) and (12) that the variance of informed demand (σ_x^2) is only dependent on the variance of uninformed demand (σ_u^2) and the ratio of uninformed to informed investors:

$$\sigma_x^2 = \beta^2 \left(\sigma_v^2 + \sigma_\varepsilon^2\right) = \frac{n}{m}\sigma_u^2. \tag{14}$$

The intuition of (14), is that the trading aggressiveness of each informed investor increases in the number of the uninformed investors, and decreases in the number of other informed investors. The distribution of the trading volume thus depends only on n, m, and σ_u and is, unlike the distribution of prices and returns, independent of σ_v and σ_ε. Given that all components of (13) follow (correlated) Normal distributions, we can find the first two moments of total trading volume from integration. We find that both the mean and the standard deviation of volume are linear in σ_u. In particular we have:

<u>Proposition 2</u>

Consider a market where n uninformed liquidity seeking traders submit Normally distributed market orders with mean zero and variance σ_u^2; m informed liquidity seeking traders, who receive noisy signals on the asset's liquidation value, submit Normally distributed market orders with mean zero and variance $\beta^2 \left(\sigma_v^2 + \sigma_\varepsilon^2\right)$; and the net order flow is absorbed by competitive liquidity suppliers. In equilibrium:

i. *The expected value of trading volume is given by:*

$$E[V] = \frac{\sigma_u}{\sqrt{2\pi}}(n + \sqrt{nm} + \sqrt{n(m+1)}). \tag{15}$$

ii. *The variance of trading volume is given by:*

$$\begin{aligned} Var(V) &= 2n\sigma_u^2 \int_0^\infty x^2(m\Phi(\sqrt{m}x) + \Phi(\frac{x}{\sqrt{mn+n-1}}))\phi(x)dx \\ &\quad + \sigma_u^2 \frac{n\sqrt{m}(1-(m+1)^{\frac{3}{2}}) + (mn+n-1)^{\frac{3}{2}} - (mn+n)^{\frac{3}{2}} - n(m+1)^2}{\pi(m+1)}, \end{aligned} \tag{16}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density function and cumulative density function *of the Standard Normal distribution.*

iii. *The coefficient of variation of trading volume is a function of n and m only. For a given number of uninformed traders n, the volume coefficient of variation increases in the number of informed traders m. For a given m, the volume coefficient of variation decreases in n.*

Proof: See Appendix A.

Panel A of Figure 1 graphically depicts the relationship between the equilibrium VCV and the number of uninformed and informed traders. For the case where $n = m = 1$ the VCV is equal to $\frac{\sqrt{3\pi-4\sqrt{2}}}{2+\sqrt{2}}$. There is no closed form solution for all other finite (n, m) combinations. The figure shows that for a given n, the equilibrium VCV is a concave increasing function of the number of informed investors. As m goes to infinity, VCV approaches $\frac{1}{2}\sqrt{2\pi - 4} \approx 0.756$, which is the coefficient of variation of the Half-Normal distribution and the VCV implied by our earlier model (Proposition 1) with $\eta = 1$. Additionally, for a given number of informed traders m, VCV is decreasing in the number of uninformed traders n. When n is very large relative to m, VCV approaches zero, as in Proposition 1 with $\eta = 0$. Panel A also shows that VCV decreases in $\frac{n}{m}$ along any diagonal with constant $(n + m)$.

Panel B of Figure 1 shows how the price elasticity of net order flow (Kyle's λ) varies with n and m. It is interesting to see that λ shows a very different pattern than VCV. Kyle's λ is not a strictly increasing function of the proportion of informed traders (for a given number of traders): moving along diagonals with constant $n + m$, we see that λ is a non-monotonic convex function of $\frac{n}{m}$. The intuition for this pattern is that an increase in the number of informed traders increases the total informed orderflow (and price informativeness), thereby lowering the price elasticity. As the number of informed traders increases further, they become less aggressive (i.e. β declines), reducing λ.

The model outlined in this subsection is one specific example of how the proportion of informed trade η is endogenously determined in equilibrium and is a function of the numbers of uninformed and informed traders only. We know also see that how the as-

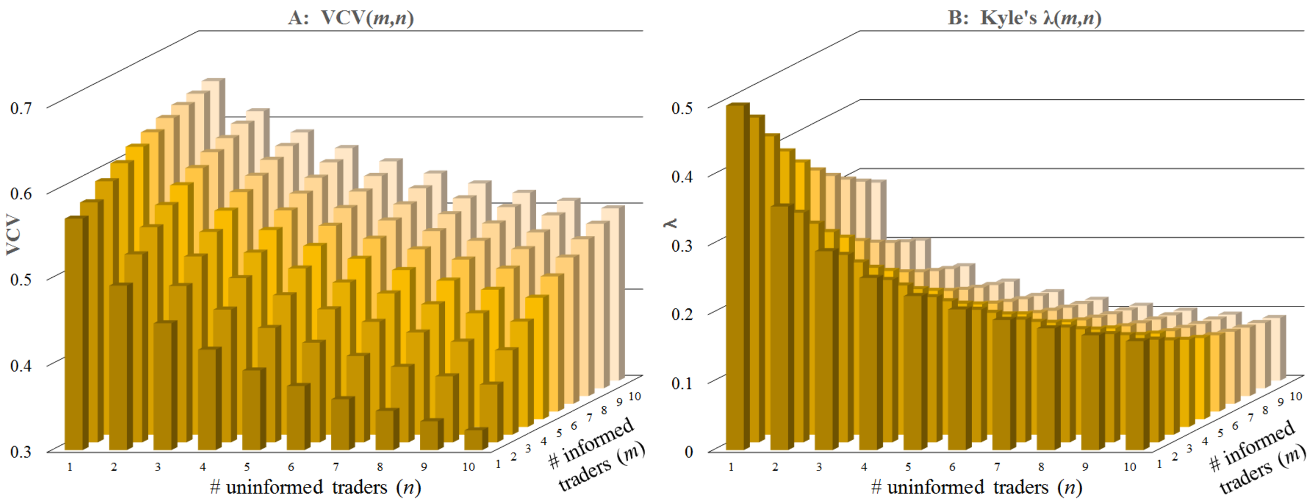

Figure 1: Equilibrium VCV (Panel A) and Kyle's λ (Panel B) as a function of n uninformed and m informed traders. Kyle's λ (Eq. 12) is divided by $\sqrt{\frac{\sigma_v^2+\sigma_\varepsilon^2}{\sigma_u^2}}$ to make it invariant to σ_ε, σ_v, and σ_u.

sumption of equal trading intensity for all traders was for convenience only, and that we can define η and M as:

$$\eta = \frac{\sigma_x m}{\sigma_x m + \sigma_u n}; \qquad M = n + \frac{\sigma_x}{\sigma_u} m. \tag{17}$$

That is, M is a measure of total *trading activity*, in which the number of individual traders are weighted by their trading intensities, while eta is the proportion of informed *trade*, rather than the proportion of informed *traders*.

If informed traders are risk neutral and receive signals with *i.i.d.* noise terms, we find from Eq.(14) that $\eta = \frac{\sqrt{nm}}{\sqrt{nm}+n}$ and $M = n + \sqrt{nm}$. Further enriching the model with risk aversion, or long lived information will change the above expressions for the equilibrium η and M, but will not change Proposition 1, as there will always be a proportion of informed trade, and an equivalent number of market participants.

3 Simulations

In this section, we analyze the distribution of trading volume generated by our model, for different values of η (proportion of informed trade) and M (equivalent number of liquidity seekers). To do this, we draw $1 + (1 - \eta)M$ random observations from the Standard

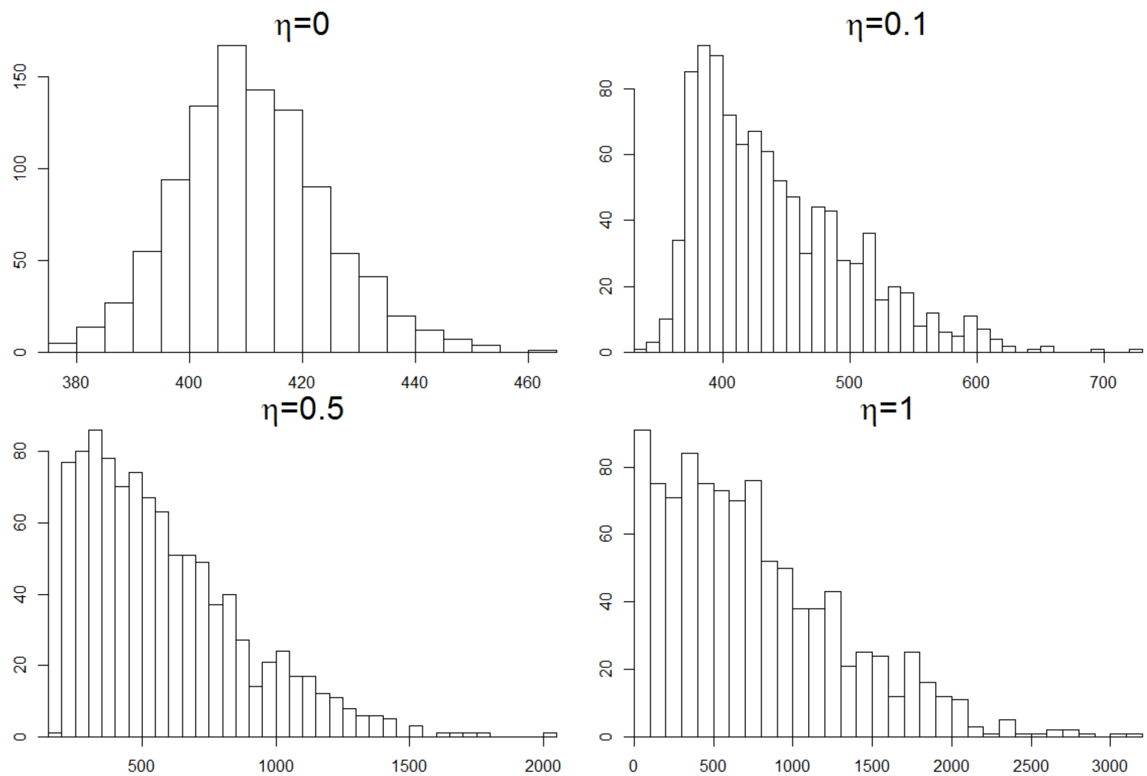

Figure 2: Histogram of T=1,000 volume realizations simulated from the model outlined in Section 2, for various values of the proportion of informed trading η. The number of liquidity seekers (M) is 1,000 and the trading intensity (σ) is fixed at unity.

Normal distribution to simulate the individual demands (i.e. we assume $\sigma = 1$). The first observation is multiplied by ηM, and represents the aggregate informed demand. The remaining observations represent the individual uninformed demands. We compute the observed trading value volume V from Eq.(1). For each (M, η) pair, we generate a sample of T volume (V) observations, from which we compute the coefficient of variation VCV.

Figure 2 displays four histograms of simulated volumes with $M = 1,000$ liquidity seekers, for different values of η. The sample size is $T = 1,000$ trading sessions. The simulation confirms the analysis in the previous section: In case of no informed traders ($\eta = 0$), the volume distribution follows a slightly skewed bell-curve, while in the presence of informed traders volume is higher in level and far more dispersed. The simulated VCVs for the four panels are 0.03, 0.14, 0.48 and 0.77, respectively.[7]

[7]The slightly skewed bell-curved volume distribution for $\eta = 0$ converges (as $M \to \infty$) to the distribution of the maximum of two Normally distributed random variables, which was first described by Clark (1961).

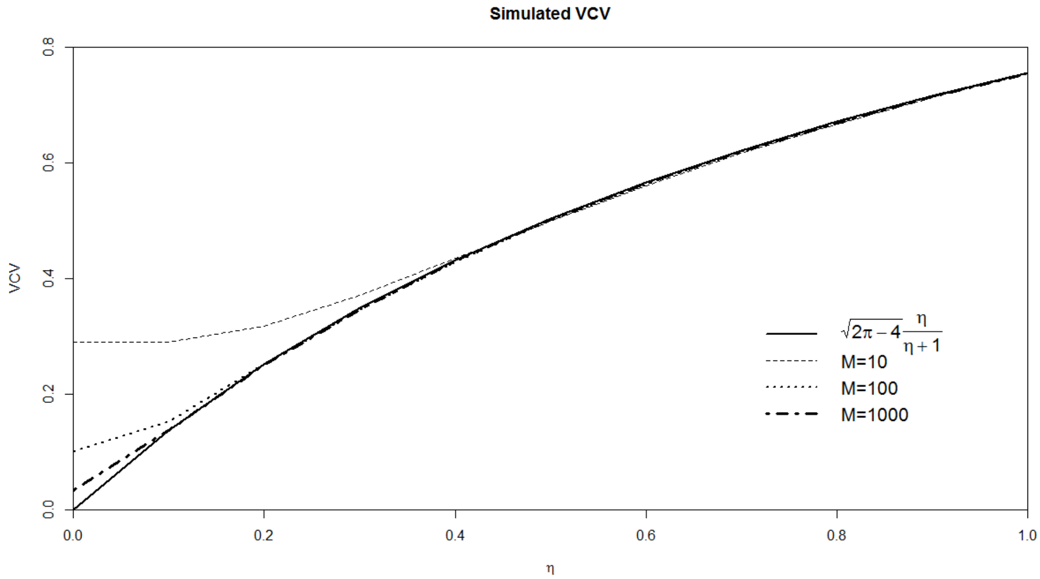

Figure 3: Average VCV obtained from $R = 1,000,000$ replications of $T = 100$ volume realizations simulated from the model outlined in Section 2, for various values of the proportion of informed trading η and number of liquidity seekers M.

Figure 3 reports the average VCV from $R = 1,000,000$ repetitions of simulating a sample of $T = 100$ trading sessions with M traders, for different values of η and M. As we see, the average VCV only deviates substantially from its theoretical value (Eq.6) when both M and η are low. Nevertheless, even for small M, the average VCV is strictly increasing in η. The insensitivity to M is encouraging as it implies that there is little concern for confounding a high η with a low M. The insensitivity to M is also desirable from an empirical perspective, because the number of traders (M) in markets is typically unknown.

In Table 1, Panel A, we report the average VCV as plotted in Figure 3 for selected values of η, as well as the standard deviations to evaluate VCV's precision. In addition to VCV, we also report these statistics on simulated values of $\widehat{\eta}$ (Eq.8). Both VCV and $\widehat{\eta}$ increase monotonically in the true proportion of informed trade (η). This is even the case for markets with low trading activity M. Also, the estimator $\widehat{\eta}$ in our simulations traces the true value of η closely, in particular when either M or η are not too low. Panel B of Table 1 reports simulation results for smaller simulated samples, of $T = 10$ trading sessions. We still find the average VCV and $\widehat{\eta}$ to increase monotonically in η, although VCV, and more

Table 1: Simulation results - Benchmark model

This table reports the average and standard deviation of VCV (left) and $\widehat{\eta}$ (right) obtained from $R = 1,000,000$ replicated samples of T volume realizations, simulated from the model outlined in Section 2, for various values of the proportion of informed trade η and number of liquidity seekers M. In Panel A, the number of volume observations in each replication is $T = 100$. In panel B, $T = 10$. Detailed simulation results are reported in Internet Appendix Tables A.1-2.

			Panel A: $T = 100$							
η	0	0.2	0.5	0.8	1	0	0.2	0.5	0.8	1
			VCV					$\widehat{\eta}$		
			$M = 10$					$M = 10$		
Avg	0.29	0.32	0.5	0.67	0.75	0.24	0.27	0.50	0.80	1.01
s.d.	0.02	0.02	0.04	0.05	0.06	0.02	0.03	0.05	0.10	0.15
			$M = 100$					$M = 100$		
Avg	0.10	0.25	0.50	0.67	0.75	0.07	0.20	0.50	0.80	1.01
s.d.	0.01	0.02	0.03	0.05	0.06	0.01	0.02	0.05	0.10	0.15
			$M = 1000$					$M = 1000$		
Avg	0.03	0.25	0.50	0.67	0.75	0.02	0.20	0.50	0.80	1.01
s.d.	0.00	0.02	0.03	0.05	0.06	0.00	0.02	0.05	0.10	0.15
			Panel B: $T = 10$							
η	0	0.2	0.5	0.8	1	0	0.2	0.5	0.8	1
			VCV					$\widehat{\eta}$		
			$M = 10$					$M = 10$		
Avg	0.28	0.31	0.48	0.65	0.74	0.23	0.26	0.49	0.81	1.27
s.d.	0.07	0.07	0.11	0.15	0.17	0.07	0.08	0.18	4.12	50.5
			$M = 100$					$M = 100$		
Avg	0.10	0.24	0.48	0.65	0.74	0.07	0.19	0.49	0.83	1.11
s.d.	0.02	0.06	0.11	0.15	0.17	0.02	0.06	0.17	0.46	3.05
			$M = 1000$					$M = 1000$		
Avg	0.03	0.24	0.48	0.65	0.74	0.02	0.19	0.49	0.78	1.16
s.d.	0.01	0.06	0.11	0.15	0.17	0.01	0.06	0.17	14.28	24.67

so $\widehat{\eta}$, are less precisely estimated.

Next, we investigate the robustness of VCV as a measure of asymmetric information by simulating trading volumes from various modified versions of our benchmark model. First, we repeat our simulation while relaxing the assumption of Normally distributed demand and allow for leptokurtic and skewed demand distributions, to generate jumps in trading volume that are unrelated to informed trading. In Table 2, Panel A, we report the average VCV and $\widehat{\eta}$ from R simulations in which liquidity demand follows a leptokurtic t-distribution with 4 degrees of freedom, or a Skew-Normal distribution with shape parameter 10 (indicating positive skewness), for selected values of η, while keeping $M = 1,000$ and $T = 100$ fixed. We find that relaxing the assumption of Normality does not change the main result of our analysis: VCV and $\widehat{\eta}$ are still strictly increasing in η. However, the standard deviations are clearly smaller for VCV than for $\widehat{\eta}$. More importantly, the average $\widehat{\eta}$ is no longer closely following the true value of η, implying that, in the case of non-Gaussian demand, $\widehat{\eta}$ should not be interpreted as a direct estimator of the true value of η. We obtain qualitatively similar results when simulating demand from a Uniform distribution, or from t- and Skew-normal distributions with different degrees-of-freedom and shape parameters.

In practice, the proportion of informed trade η is not necessarily constant across observations, and we are typically interested in measuring the *average* proportion of informed trade, over either a time series or a cross section of observations. To gauge the precision of our measures in this context, we repeat the simulation analysis while allowing the proportion of informed trade η to be random across observations. This version of our model can be interpreted as a hybrid of our Kyle (1985)-type model in Section 2 and the PIN model by Easley et al. (1996), in which arrival of information is random, similar to the model by Back et al. (2018). Panel B of Table 2 reports simulation results for the case where the number of uninformed liquidity seekers is fixed at 1,000, while the number of informed liquidity seekers is in each of the $T = 100$ trading sessions randomly drawn from a Bernoulli distribution. The number of active informed traders in each trading session is equal to X with probability $\frac{1}{5}$ and zero with probability $\frac{4}{5}$, such that the informed traders participate in only one out of five trading sessions on average. To create variation in the average proportion of informed trade, we adjust the potential number of informed traders X. In this setting, $\widehat{\eta}$ clearly does not perform well as a measure of informed trading. The simulated observations of $\widehat{\eta}$ are widely dispersed, while their averages are not

Table 2: Simulation results - Robustness

This table reports the average and standard deviation of VCV (left) and $\widehat{\eta}$ (right) obtained from $R = 1,000,000$ replicated samples of $T = 100$ volume realizations, simulated from various generalizations of the model outlined in Section 2, with $M = 1000$ liquidity seekers, for various values of the proportion of informed trading η. In Panel A, demand is t-distributed with 4 degrees of freedom (t_4), or Skew-Normally distributed with shape parameter 10, indicating positive skew ($SN(0,1,10)$). In Panel B, the number of uninformed liquidity seekers is kept constant at $1,000$, while the number of informed liquidity seekers is varying randomly across observations and follows a Bernoulli distribution such that the number of active informed traders in each trading session is with probability $\frac{4}{5}$ equal to zero and with probability $\frac{1}{5}$ equal to X. The table reports the average VCV and $\widehat{\eta}$ for different values of X, which determines the average proportion of informed trade $E[\eta]$.

Panel A: Non-Gaussian demand distributions										
η	0	0.2	0.5	0.8	1	0	0.2	0.5	0.8	1
			VCV					$\widehat{\eta}$		
			t-distribution					*t-distribution*		
Avg	0.04	0.32	0.64	0.86	0.97	0.03	0.28	0.78	1.23	1.60
s.d.	0.00	0.07	0.12	0.15	0.16	0.00	0.29	7.57	81.28	48.82
			Skew-Normal distribution					*Skew-Normal distribution*		
Avg	0.02	0.15	0.38	0.61	0.75	0.02	0.11	0.34	0.67	1.01
s.d.	0.00	0.01	0.03	0.04	0.06	0.00	0.01	0.03	0.08	0.15
Panel B: Random proportion of informed trade [*Informed investors* $\sim B(1/5, X)$]										
X	0	1250	5000	20000	125000	0	1250	5000	20000	125000
$E[\eta]$	0	0.2	0.5	0.8	0.96	0	0.2	0.5	0.8	0.96
			VCV					$\widehat{\eta}$		
Avg	0.03	0.83	1.70	2.32	2.59	0.02	1.28	-13.8	-3.09	-2.56
s.d.	0.00	0.10	0.15	0.26	0.34	0.00	0.35	3861.71	0.80	0.55

monotonically increasing in $E[\eta]$, and are not bounded by 0 and 1. This poor performance of $\widehat{\eta}$ occurs because the denominator in Eq.(8) can easily take on small or negative numbers, which makes the estimator highly erratic. VCV, on the other hand, continues to be monotonically increasing in $E[\eta]$ while its standard deviations remain fairly low. These results are robust to various alternative distributions for the number of active informed investors.

Overall, the simulation results in this section demonstrate the robustness of VCV as a measure of asymmetric information. The basic result that the coefficient of variation of trading volume is monotonically increasing in the proportion of informed trade holds under general conditions and in small samples. Additional simulation results are presented in Internet Appendix A. These simulations are based on further variations of the basic model including random variation in the number of market participants and their trading intensities across observations, heterogeneity among the informed investors, and endogenous informed demand. These supplementary results provide further evidence for the robustness of VCV. In the remainder of this paper, we therefore focus on VCV as our measure of informed trade, and investigate its properties using real empirical data.

4 The Cross-Section of VCV

After having established from theoretical and numerical analysis a positive monotonic relation between VCV and the proportion of informed trade, we now turn to the data to analyze the empirical properties of VCV. In this section, we describe cross-sectional variation in VCV for US stocks, while we study the time-series behavior in the next section. We compute annual Volume Coefficients of Variation (VCV) for US stocks and compare these figures with other firm-level characteristics, including indicators of informed trade and illiquidity. We obtain daily trading volumes from the CRSP daily stock file for all common stocks listed on NYSE, AMEX and NASDAQ over the period 1980-2016. We disregard the most infrequently traded stocks by only including firm-year observations for stocks with positive trading volume in at least 200 days during that year.[8]

Annual firm-level observations of VCV are computed by dividing the annual standard deviation of daily trading volumes by the annual average of daily trading volumes. The volume coefficient of variation of stock i in year τ is defined as:

[8]For NASDAQ listed firms, we adjust trading volume prior to 2004 following Gao and Ritter (2004): reported volume on NASDAQ stocks is divided by 2.0, 1.8, and 1.6 during the period prior to February 1st 2001, the period between February 1st 2001-December 31st 2001, and January 1st 2002 - December 31st 2003, respectively. Note that this adjustment does not affect VCV, in which volume is both in the nominator and denominator, but it does affect other measures that are based on volume, such as Amihud (2002) Illiquidity.

$$VCV_{i,\tau} = \frac{\hat{\sigma}_{V(i,t\in\tau)}}{\hat{\mu}_{V(i,t\in\tau)}}, \tag{18}$$

where $\hat{\mu}_{V(i,t\in\tau)}$ is the sample average and $\hat{\sigma}_{V(i,t\in\tau)}$ is the sample standard deviation of all daily trading volumes of stock i, $V_{i,t}$, in year τ. We compute VCV using three different measures of trading volume: trading volume in US dollars:

$$V_{USD,i,t} = shares\ traded_{i,t} \times closing\ price_{i,t}, \tag{19}$$

volume *market shares*, defined as daily volume in a single stock as a fraction of total market volume on the same day, to control for market-wide variation in trading-activity that is unrelated to firm-specific information, such as macro-level sentiment and liquidity shocks:

$$V_{\%,i,t} = \frac{V_{USD,i,t}}{\sum_i V_{USD,i,t}}, \tag{20}$$

and daily *turnover*, to control for differences in market capitalization:

$$V_{TO,i,t} = \frac{shares\ traded_{i,t}}{shares\ outstanding_{i,t}}. \tag{21}$$

Table 3 reports summary statistics for these three measures of VCV. The sample averages, as well as other statistics, are highly similar for the three distinct VCV measures. The bottom rows of Table 3 show that the three different measures of VCV are highly correlated. The strong similarity between the three VCV measures offers support for the theoretical analysis of Section 2: although trading intensity (σ) and participation (M) are determinants of the level and variance of volume, VCV is independent of both σ and M (Eq.(6)). Market-wide variation in the number of market participants and their trading intensity should therefore have little impact, so that VCV derived from dollar volume, volume market shares, or turnover, are virtually equivalent. The results in Table 3 support this premise. In the remainder of this section, our measure of informed trading VCV is de-

Table 3: VCV Summary Statistics

This table reports summary statistics of annual firm-level observations of the Volume Coefficient of Variation (VCV) of daily dollar trading volume in US dollars (VCV_{USD}), daily volume market shares (daily dollar volume as a percentage of total market dollar volume – $\text{VCV}_{\%}$), and turnover (dollar volume as a fraction of market capitalization – VCV_{TO}). The table reports the total number of observations, the number of distinct stocks in the sample (N), the number of time-series observations/years (T), mean, standard deviation, s.d. (CS), the time-series average of annual cross-sectional standard deviations, s.d. (TS), the cross-sectional average of stock-specific time-series standard deviations, selected quantiles (q), and the cross-sectional average of stock-specific first-order autocorrelations (ρ). The bottom two rows report the time-series averages of within-year rank (Spearman) correlations between the different VCV measures. Sample: 1980-2016.

	VCV_{USD}	$\text{VCV}_{\%}$	VCV_{TO}
Observations	$137,522$	$137,522$	$137,522$
N	$15,918$	$15,918$	$15,918$
T	37	37	37
Mean	1.362	1.343	1.310
s.d.	0.798	0.811	0.748
s.d. (CS)	0.762	0.773	0.720
s.d. (TS)	0.536	0.540	0.506
$q_{0.1}$	0.594	0.556	0.586
$q_{0.25}$	0.840	0.814	0.817
Median	1.215	1.200	1.164
$q_{0.75}$	1.650	1.641	1.583
$q_{0.9}$	2.224	2.213	2.146
ρ	0.172	0.178	0.189
Correlations			
$\text{VCV}_{\%}$	0.983		
VCV_{TO}	0.970	0.959	

fined as the annual coefficient of variation of daily volume market shares ($\text{VCV}_{\%}$), which controls for market-wide variation in volume that is unrelated to firm-specific information. Highly similar results are obtained when using any of the other volume definitions. In the Internet Appendix Table B.1, we report the VCV summary statistics for subsamples of stocks listed on NASDAQ and stocks listed on NYSE/AMEX, and for subsamples of observations prior to 2000 (1980-1999) and post 2000 (2000-2016), showing that the three measures of VCV behave fairly similar across these subsamples.

Table 4: VCV and other firm characteristics

This table reports the correlations between annual firm-level observations of VCV (obtained from daily volume market shares) and other annual firm-level characteristics. Each entry reports the time-series average of within-year rank (Spearman) correlations. *Size* is the log of market capitalization at the last trading day of June. *BM ratio* is the ratio of the book value to the market value of equity. *Age* is the number of years since the firm's first appearance in CRSP. *Volatility* is the annual standard deviation of daily returns. *Turnover* is the annual average of daily trading volume as a percentage of market capitalization. *Illiquidity* is the log of the annual average of the daily ratio $\frac{|R_{i,t}|}{V_{USD,i,t}}$ (Amihud, 2002). *Bid-Ask spread* is the annual average of daily bid-ask spreads $\frac{ask_{i,t}-bid_{i,t}}{price_{i,t}}$. *Roll's measure* is the square root of the negative of the daily return autocovariance $\sqrt{-Cov\left(R_{i,t},R_{i,t-1}\right)}$. *Coverage* refers to the number of distinct analysts covering a stock in a given year Sample: 1980-2016. Source: CRSP, COMPUSTAT, and IBES.

	VCV	Size	BM	Age	Vol.	Turn.	Illiq	B-A	Roll
Size	−0.64								
BM ratio	0.17	−0.22							
Age	−0.29	0.34	0.11						
Volatility	0.38	−0.61	−0.04	−0.40					
Turnover	−0.31	0.33	−0.21	−0.02	0.16				
Illiquidity	0.68	−0.94	0.22	−0.33	0.55	−0.52			
Bid-Ask spread	0.62	−0.87	0.25	−0.24	0.61	−0.42	0.91		
Roll's measure	0.25	−0.36	0.19	−0.05	0.24	−0.30	0.41	0.52	
Coverage	−0.58	0.79	−0.25	0.19	−0.32	0.47	−0.81	−0.71	−0.29

4.1 VCV and other firm characteristics

Table 4 reports the correlations between VCV and other firm-level characteristics: size, book-to-market ratio, firm age, return volatility, turnover, Amihud (2002) illiquidity, bid-ask spread, Roll's (1984) estimate of the bid-ask spread, and analyst coverage. Size is defined as the log of market capitalization on the last trading day of June. Return volatility is the annual standard deviation of daily returns. Amihud (2002) illiquidity is defined as the the log of the annual average of the daily ratio $\frac{|R_{i,t}|}{V_{USD,i,t}}$. The bid-ask spread is the annual average of daily closing bid-ask spreads as a percentage of the closing price $\frac{ask_{i,t}-bid_{i,t}}{price_{i,t}}$. Roll's (1984) measure is the square root of the negative of the daily return autocovariance $\sqrt{-Cov\left(R_{i,t},R_{i,t-1}\right)}$.[9] The book-to-market ratio is the ratio of the book value of equity

[9] In the case of positive return autocorrelations, we set Roll's measure equal to $-\sqrt{Cov\left(R_{i,t},R_{i,t-1}\right)}$, following Roll (1984). We obtain qualitatively similar results when we either set these observations of Roll's measure to zero, or omit them from our sample.

at the fiscal year end, obtained from COMPUSTAT, to the market value of equity at the end of the same calendar year. Firm age is proxied by the number of years passed since the firm appeared for the first time in the CRSP database. Analyst coverage is defined as the number of distinct analysts covering a stock in a given year (Source: IBES). Summary statistics of these variables and subsample analyses are provided in Internet Appendix Tables B.2 and B.3.

As can be seen from Table 4, VCV is negatively correlated to size and turnover and positively correlated to return volatility, Amihud illiquidity and the bid-ask spread. These results are consistent with our proposition that VCV is a measure of informed trading, since information asymmetry is likely to be stronger in smaller stocks and asymmetric information reduces liquidity. The negative correlation with firm age suggest that information asymmetry is lower for more mature firms. Analyst coverage is likely to reduce information asymmetry, which is consistent with the negative correlation with VCV. In Section 5, we study the impact of exogenous reductions in analyst coverage due to brokerage closures and find that reductions in analyst coverage are associated with an increase in VCV.

4.2 Return reversals

The correlation between VCV and the bid-ask spread reported in Table 4, is clearly higher than the correlation between VCV and Roll's (1984) estimate of the bid-ask spread. This result is expected, as it is well known from Huang and Stoll (1997) and others, that Roll's measure underestimates the bid-ask spread in the presence of information asymmetries, since price changes due to informed trading are less likely to be reversed by the bid-ask bounce, and are characterized by less negative autocorrelations. To further evaluate the relationship between VCV and the bid-ask spread, we double-sort stocks within each year into quartiles based on the bid-ask spread and on Roll's measure. Table 5 shows the average VCV for each of these sixteen groups of firms. We find that VCV is monotonically increasing in the bid-ask spread but not in Roll's measure, which is consistent with the

Table 5: VCV and the Bid-Ask spread

This table reports the sample average VCV for 16 groups of stocks double-sorted within each year on the *Bid-Ask spread* (the annual average of daily bid-ask spreads $\frac{ask_{i,t}-bid_{i,t}}{price_{i,t}}$) and *Roll's* (1984) measure (the square root of the negative of the daily return autocovariance $\sqrt{-Cov\left(R_{i,t}, R_{i,t-1}\right)}$). The final row and column report the difference in average VCV between high and low quartiles, with significant differences at the 10%, 5%, and 1% level indicated by *, **, and ***. Source: CRSP.

	Roll: Low	2	3	High	High-Low
Bid-Ask: Low	0.949	0.803	0.748	0.949	−0.001
2	1.157	1.114	1.114	1.018	−0.139**
3	1.384	1.350	1.488	1.404	0.020
High	1.949	1.717	1.822	2.015	0.067*
High-Low	0.999***	0.914***	1.074***	1.067***	0.067

downward bias of Roll's measure in the presence of information asymmetry. Stocks with high information asymmetry are expected to have a relatively high bid-ask spread but a relatively low value of Roll's measure. We see from Table 5 that these stocks are precisely the stocks with a high VCV.

To further study the relation between VCV and return autocorrelation, we consider weekly return reversals. It is well known that returns on individual stocks, in particular illiquid stocks, exhibit significant short-term reversals (e.g. Jegadeesh, 1990). We compute weekly return autocorrelations for each firm within each year in our sample. We then double-sort stocks within each year into quartiles based on Amihud's (2002) Illiquidity and VCV. In Table 6, we report the average weekly return autocorrelation, for each of these 16 groups. Across all 16 groups, we find return reversals (i.e. negative autocorrelation). These reversals are stronger for the more illiquid stocks. However, within each liquidity quartile, we find that reversals are decreasing in VCV. The final column of Table 6 shows that return autocorrelation is lower for High VCV stocks than for Low VCV stocks. This result implies, similar to Table 5, that short-term reversals are in general more profound for illiquid stocks, but that these reversals are weaker when the illiquidity is associated with information asymmetry.

Table 6: VCV and weekly reversals

This table reports the sample average of weekly return autocorrelations for 16 groups of stocks double-sorted within each year on Amihud (2002) *Illiquidity* and *VCV*. The final row and column report the difference in average weekly return autocorrelations between high and low quartiles, with significant differences at the 10%, 5%, and 1% level indicated by *, **, and ***. Source: CRSP.

	Illiq: Low	2	3	High	High-Low
VCV: Low	-0.058	-0.065	-0.087	-0.102	-0.044^{***}
2	-0.047	-0.046	-0.065	-0.094	-0.046^{***}
3	-0.039	-0.039	-0.049	-0.084	-0.045^{***}
High	-0.040	-0.028	-0.040	-0.081	-0.041^{***}
High-Low	0.018^{**}	0.037^{***}	0.047^{***}	0.021^{*}	0.003

The results reported in this section are qualitatively similar across exchanges and in different time periods. Subsample analyses are reported in Internet Appendix Tables B.4 and B.5. These results are also consistent with existing research: Llorente et al. (2002), Hameed et al. (2008), Bongaerts et al. (2016), and Johnson and So (2018) use various measures to show that asymmetric information is associated with weaker short-term reversals. In the next subsection, we have a closer look at the empirical relation between VCV and existing measures of asymmetric information.

4.3 VCV and other measures of asymmetric information

In this subsection, we compare VCV with various incumbent measures of asymmetric information. These measures include the probability of informed trade (PIN; Easley et al., 1996), C2 (Llorente et al., 2002), and the Multimarket Information Asymmetry measure (MIA; Johnson and So, 2018). PIN is estimated by fitting a structural microstructure model to signed transaction data. C2 measures the relation between daily volume and return persistence, based on the premise that price changes due to informed trading are predictive of future price changes. MIA is based on relative trading volume in options and stocks, based on the assumption that informed traders are more likely to trade in options.

For our analysis, we make use of the various PIN and MIA measures that are kindly

Table 7: VCV and other information asymmetry measures

This table reports the correlation between the annual firm-level coefficients of variation of daily volume market shares (VCV) and various annual firm-level information asymmetry measures. Each entry reports the time-series average of within-year rank (Spearman) correlations. PIN_{BHL} is estimated by Brown, Hillegeist and Lo (2004). PIN_{BH} is estimated by Brown and Hillegeist (2007). PIN_{EHO} is estimated by Easley, Hvidkjaer, and O'Hara (2010). PIN_{DY}, Adjusted PIN, and the illiquidity measure PSOS are estimated by Duarte and Young (2009). MIA is the annual average of firm-day level observations estimated by Johnson and So (2017). C2 is estimated following Llorente et al. (2002). Sources: CRSP and cited authors' websites.

	VCV	PIN_{BHL}	PIN_{BH}	PIN_{EHO}	PIN_{DY}	Adj.PIN	PSOS	MIA
PIN_{BHL}	0.53							
PIN_{BH}	0.60	0.74						
PIN_{EHO}	0.53	0.62	0.68					
PIN_{DY}	0.57	0.65	0.69	0.86				
Adjusted PIN	0.52	0.58	0.71	0.64	0.72			
PSOS	0.46	0.45	0.44	0.62	0.71	0.39		
MIA	0.26	0.37	0.44	0.12	0.24	0.32	0.05	
C2	0.10	0.12	0.11	0.03	0.03	0.04	0.04	0.02

made publicly available by the authors of previous studies. These measures include MIA estimated by Johnson and So (2018) and PIN measures estimated by Easley et al. (2010 – PIN_{EHO}); Brown, Hillegeist and Lo (2004 – PIN_{BHL}); Brown and Hillegeist (2007 – PIN_{BH}); and Duarte and Young (2006 – PIN_{DY}).[10] We compute annual firm-level observations of MIA as the annual average of the available daily observations for each firm. We derive annual stock-level observations of C2 as the estimated slope coefficient from running regressions, for each firm in each year, of daily returns on the interaction of lagged returns and lagged (detrended) turnover, while controlling for daily lagged returns (see Llorente et al., 2002, for details).

Table 7 shows the correlations between VCV and various annual firm-level information asymmetry measures. Our VCV measure is positively correlated to all PIN measures.

[10] Annual firm-level observations of PIN_{DY}, PIN_{EHO}, PIN_{BH} and PIN_{BHL} are made available by Jefferson Duarte (`http://www.owlnet.rice.edu/~jd10/`), Søren Hvidkjær (`https://sites.google.com/site/hvidkjaer/data`) and Stephen Brown (`http://scholar.rhsmith.umd.edu/sbrown/pin-data`), respectively. Daily firm-level observations of MIA are made available by Travis Johnson (`http://travislakejohnson.com/data.html`). Summary statistics of the measures employed in this section, as well as subsample analyses, are provided in Internet Appendix Tables B.6-B.8.

Table 8: VCV and Adjusted PIN

This table shows the results from regressing annual firm-level coefficients of variation of daily volume market shares (VCV) on the measures by Duarte and Young (2009): PIN_{DY}, Adjusted PIN, and PSOS (probability of symmetric order-flow shock). All regressions include fixed effects for each year, industry, size decile, book-to-market decile and Illiquidity decile. Two-way clustered standard errors, clustered at the year and industry level, are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level. Source: CRSP and the website of Jefferson Duarte (`http://www.owlnet.rice.edu/~jd10/`)

	VCV			
	(1)	(2)	(3)	(4)
PIN_{DY}	0.448***		0.961***	0.506***
	(0.125)		(0.164)	(0.112)
Adjusted PIN	0.957***	1.186***		0.924***
	(0.158)	(0.181)		(0.162)
PSOS	0.049	0.188***	−0.129**	
	(0.055)	(0.052)	(0.059)	
Observations	37,986	37,986	37,986	37,986
Adjusted R^2	0.357	0.356	0.353	0.357
Fixed effects	Yes	Yes	Yes	Yes

The correlation between VCV and PIN is of similar magnitude as the correlations between the various PIN measures. Compared to these PIN measures, however, our VCV measure is far easier to compute and does not require intraday data on the order process. The correlations between VCV and the MIA and C2 measures are substantially lower, although still positive.

Duarte and Young (2009) argue that PIN does not only measure informed trading, but also other illiquidity effects. They therefore decompose PIN into *Adjusted PIN*, which is proposed as a cleaner measure of asymmetric information; and *PSOS* (probability of symmetric order-flow shock), which is a measure of illiquidity unrelated to asymmetric information. These additional variables are included in Table 7. Both Adjusted PIN and PSOS are positively correlated with VCV.

In Table 8, we examine the correlation between VCV and the three measures by Duarte and Young (2009) in a regression context. To control for time variation and firm characteristics unrelated to asymmetric information, we include year fixed effects, 48 Fama-French industry fixed effects, and decile fixed effects for size, book-to-market and Amihud illiquidity deciles.[11] The regression results indicate that VCV is mostly associated with adjusted PIN, while there is no robust relation between VCV and PSOS, thereby supporting our claim that VCV, like adjusted PIN, is indicative of asymmetric information rather than general illiquidity.

4.4 VCV and institutional ownership

In this subsection, we study the relationship between VCV and various indicators of institutional ownership that we obtain from 13F filings recorded in the Spectrum database. Table 9 reports the results from regressing VCV on various institutional ownership characteristics. These characteristics include institutional holdings (defined as the percentage of shares of a firm held by institutional investors at the end of the year) and breadth of ownership (defined as the number of institutional investors holding shares in the firm, as a percentage of the total number of institutional investors reported in the Spectrum 13F database at the end of each year – Chen et al., 2002). Boone and White (2015) find that institutional ownership leads to an improvement in disclosure practices and therefore lower information asymmetry. The first column of Table 9 shows indeed that VCV has a significantly negative association with breadth of ownership. VCV is lower (implying lower information asymmetry) for firms that have high breadth of ownership.

In addition, we consider two measures that identify groups of presumably well-informed investors: monitoring investors and dedicated investors. Following Fich et al. (2015), we define an institutional investor to be a 'monitor' for a certain firm if that firm belongs to the top 10% of holdings in the institution's portfolio. These monitoring investors are likely to be better informed about the firm than non-monitoring investors. Dedicated investors

[11]Rather than including size, book-to-market and illiquidity as control variables, we control for these characteristics using decile fixed effects, in order to accommodate nonlinearities and outliers.

Table 9: VCV and institutional ownership

This table reports the results from regressing annual firm-level coefficients of variation of daily volume market shares (VCV) on various measures of institutional ownership. *Holdings* is the percentage of shares of the firm held by institutional investors at the end of the year; *Breadth* is the percentage of all institutional investors that hold shares of the firm (Chen et al., 2002); $Monitors$ is the fraction of institutional investors in each firm for which the firm is in the top 10% of the institution's holdings (Fich et al., 2015); and *Dedicated* is the fraction of institutional investors in each firm that are classified as 'Dedicated' investors by Bushee and Noe (2000). All regressions include fixed effects for each year, industry, size decile, book-to-market decile and illiquidity decile. Two-way clustered standard errors, clustered at the year and industry level, are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level. Sources: CRSP, 13F and the website of Brian Bushee `http://acct.wharton.upenn.edu/faculty/bushee/`

	VCV			
	(1)	(2)	(3)	(4)
Holdings	−0.0003	−0.0004	−0.0003	−0.0004
	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Breadth	−1.125***	−1.732***	−1.102***	−1.677***
	(0.070)	(0.115)	(0.072)	(0.113)
Monitors		1.011***		0.973***
		(0.155)		(0.155)
Dedicated			0.311***	0.308***
			(0.082)	(0.079)
Observations	83,339	83,339	77,225	77,225
Adjusted R^2	0.408	0.409	0.406	0.407
Fixed effects	Yes	Yes	Yes	Yes

are those institutional investors that Bushee and Noe (2000) and Bushee (2001) classify as 'dedicated'. They are characterized by large, stable holdings in a small number of firms, as opposed to 'quasi-indexing' investors and 'transient' investors.[12]

The variable *Monitors* in Table 9 is the percentage of institutional investors in each firm that are defined as monitoring investors. The variable *Dedicated* in Table 9 is the percentage of institutional investors in each firm that are classified as dedicated investors. Columns 2–4 of Table 9 show that these variables are both significantly positively associated with

[12]Classification into these three groups is based on a factor and cluster analysis approach (see Bushee, 2001, for details). The classification of institutional investors in the 13F Spectrum database is made available on the website of Brian Bushee `http://acct.wharton.upenn.edu/faculty/bushee/`.

VCV, consistent with our proposition that VCV measures informed trade.

The relationship between patterns in institutional ownership and VCV reported in Table 9 reaffirms that VCV is a measure of asymmetric information. Suppose that a firm is held by only a small number of institutional investors, who each assign a relatively large fraction of their portfolio to this firm's stock (i.e. *Breadth* is low, while *Monitors* and *Dedicated* are high). Ownership of such a firm is therefore relatively concentrated in the hands of a small number of presumably well informed investors. When trading this firm, information asymmetry should be a significant concern, as it is likely that the counter party is one of these better informed investors. On the other hand, for a firm that is widely held among institutional investors, each of which holding only a relatively small share of the firm (i.e.: *Breadth* is high, while *Monitors* and *Dedicated* are low), the risk of asymmetric information should be lower, which is in accordance with the results reported in Table 9. Summary statistics of the measures employed in this section, as well as subsample analyses, are provided in Internet Appendix Tables B.9-B.10.

5 VCV around information events

After having analyzed cross-sectional variation in VCV, we now study the behavior of VCV over time. The solid black line in Figure 4 shows the cross-sectional average of the firm-level VCVs (derived from volume market shares), for each year in our sample analyzed in Section 4. The gray bars show the cross-sectional average of the firm-level mean and standard deviation of volume market shares. The declining trend of VCV post-2000 suggests that asymmetric information has reduced over this period, which is consistent with recent studies (e.g. Duarte at al., 2008; Lambert et al., 2012; Horton et al., 2013) that document improved market transparency as the result of regulatory changes, such as the enactment by the SEC in 2000 of Regulation Fair Disclosure (Reg FD) and the adoption of International Financial Reporting Standards (IFRS). In Internet Appendix Figure B1, we

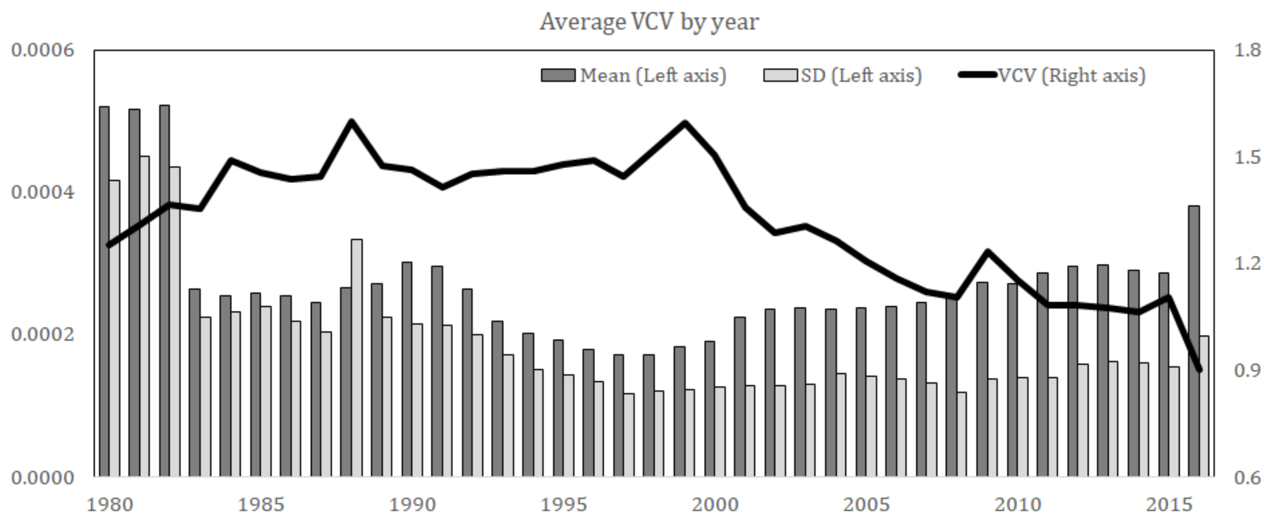

Figure 4: The black line shows the annual cross-sectional average of annual firm-level VCVs, calculated from volume market shares (Eq.(20)) over the period 1980-2016. The bars show the annual cross-sectional average of annual firm-level means and standard deviations of volume market shares.

reproduce this graph for firm-level VCVs computed from dollar volume and turnover, showing once again that VCV is highly similar for the three volume measures.[13]

In the remainder of this section, we study the behavior of VCV around information events. First, we exploit a natural experiment to identify exogenous changes in information asymmetry: brokerage closures. Various recent studies (e.g. Kelly and Ljungqvist, 2012; Derrien and Kecskes, 2013) consider terminations of analyst coverage due to brokerage closures as exogenous shocks to the information environment of individual stocks. Consistent with the hypothesis that information asymmetry increases following such reductions in analyst coverage, we document an increase in VCV. Next, we analyze VCV around quarterly earnings announcements and find that VCV is relatively high shortly before, and significantly lower after announcements.

5.1 VCV around brokerage closures

Kelly and Ljungqvist (2012) find that information asymmetry increases following terminations in analyst coverage that are caused by exogenous closures or acquisitions of bro-

[13]The level shift in the means and standard deviation of volume shares after 1982 occurs because of the inclusion of NASDAQ shares.

kerage firms. For the 22 brokerage closures between April 2000 and January 2008 listed in Appendix A of Kelly and Ljungqvist (2012), we identify in the IBES database a treatment sample of a total of 1,764 observations of firms that experience reductions in analyst coverage due to one of these closures.

We perform a simple difference-in-differences regression, to compare the VCV of treated firms (i.e. firms that experience closure-induced coverage terminations) to non-treated firms (the control group), before and after the brokerage closure. For each brokerage closure, our control group includes all non-treated firms in our sample analyzed in Section 4, for which analyst coverage in the calendar year prior to the brokerage closure is strictly positive. The VCV before closure is defined as the coefficient of variation of daily volume market shares over a 12-month period before the closure, while the VCV after closure is calculated over a 12-month period after the closure. Following Derrien and Kecskes (2013), we impose three-month gaps between the event and the estimation windows, such that the VCV before (after) closure is calculated from trading volumes over the months -14 to -3 (+3 to +14), with the brokerage closure occurring in month 0. These observations of VCV are regressed on a dummy variable indicating observations in the *treatment* group, a dummy variable indicating the observations *after* each brokerage closure, and an interaction term of the two dummy variables.

The results of the difference-in-differences regression are reported in the first column of Table 10. The coefficient on the interaction term *After*×*Treated* is of primary interest. This interaction coefficient is positive and significant, meaning that the VCV of firms that face exogenous analyst reductions as a result of brokerage closures *increases* relative to the VCV of control firms that are not exposed to the brokerage closures. The coefficient on *After* is negative, which reflects that VCV is on average decreasing over time, as can be seen from Figure 4. The *Treated* coefficient indicates that there is a minor difference between the VCV of treated and control firms, prior to the event.[14]

The second and third column of Table 10 show that the interaction coefficient becomes larger when we restrict the sample to firms with low analyst coverage. The intuition behind this result is that the event of one analyst discontinuing coverage of a firm is a greater disruption to the information environment when the firm has already low analyst coverage to begin with. Indeed, the difference-in-differences estimate is approximately doubled (tripled) when covering only firms with analyst coverage of less than 10 (5) in the calendar year prior to the event. Overall, the results in Table 10 provide strong evidence for our proposition that VCV measures information asymmetry.

5.2 VCV around earnings announcements

In this subsection we look at the VCV computed from the cross section of volume. In particular, we document the pattern of the cross-sectional VCV around earnings announcements It is widely recognized that earnings announcements resolve information asymmetries (e.g. Chae, 2005; George et al., 1994). In this section we show that, consistent with this view, VCV is relatively high prior to announcements and low afterwards, suggesting that uninformed traders delay their trades until information asymmetries are resolved after the announcement.

We obtain $N = 339,257$ quarterly earnings announcement dates from COMPUSTAT, for a total of $13,885$ distinct NYSE, AMEX, and NASDAQ listed US firms over the period 1980-2016. To evaluate the evolution of information asymmetry in event time, we introduce the so-called *cross-sectional VCV* for each day around the announcement date. We calculate the coefficient of variation at day $d \in [-30, 30]$ around the event date, using the N daily trading volumes of each stock on d days after the firm's earning announcement

[14]In Internet Appendix Tables B.11-B12, we report results for VCV computed over a 6-month period, and for a regression with a smaller control sample matched on firm size and analyst coverage, and find qualitatively similar results.

Table 10: Brokerage closures

This table reports the results from difference-in-differences regressions around brokerage closure-induced terminations of analyst coverage. The treatment sample consist of 1,764 observations of firms that experience a reduction in analyst coverage due to a total of 22 distinct brokerage closures between April 2000 and January 2008. The control sample consists of 31,661 observations. For all 33,425 observations, we compute VCV over the months $[-14, -3]$, and over the months $[3, 14]$, with the brokerage closure occurring in month 0, resulting in a total of 66,850 observations of VCV. These VCVs are regressed on dummies indicating the treatment group (Treated), the post-closure window (After), and their interaction. In the second (third) column, the sample is restricted to firms with analyst coverage of less than 10 (5) in the calendar year prior to the closure. All regressions include fixed effects for each year, industry, size decile, book-to-market decile and illiquidity decile. Two-way clustered standard errors, clustered at the year and industry level, are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Full sample	Coverage < 10	Coverage < 5
	VCV	VCV	VCV
After × Treated	0.035***	0.051**	0.113***
	(0.007)	(0.020)	(0.040)
After	−0.081***	−0.090***	−0.097***
	(0.009)	(0.010)	(0.011)
Treated	−0.024**	−0.022*	−0.045
	(0.011)	(0.012)	(0.031)
Observations	66,850	46,952	27,760
Adjusted R^2	0.401	0.395	0.434
Fixed effects	Yes	Yes	Yes

announcement date:

$$VCV_{XS,d} = \frac{\hat{\sigma}_{V(t=t_i+d)}}{\hat{\mu}_{V(t=t_i+d)}}, \tag{22}$$

where $\hat{\mu}_{V(t=t_i+d)}$ is the sample average and $\hat{\sigma}_{V(t=t_i+d))}$ is the sample standard deviation of N daily trading volumes on day d after the firm-specific announcement date t_i. All volumes are as before defined as volume market shares, $V_{\%i,t}$, i.e.: volumes as a percentage as total trading volume on that calendar date t.

This cross-sectional VCV is computed for all days d over the interval from -30 days before the announcement to +30 days after the announcement. The black line in Figure 5 shows the pattern of VCV over this interval, while the shaded areas indicate 95%

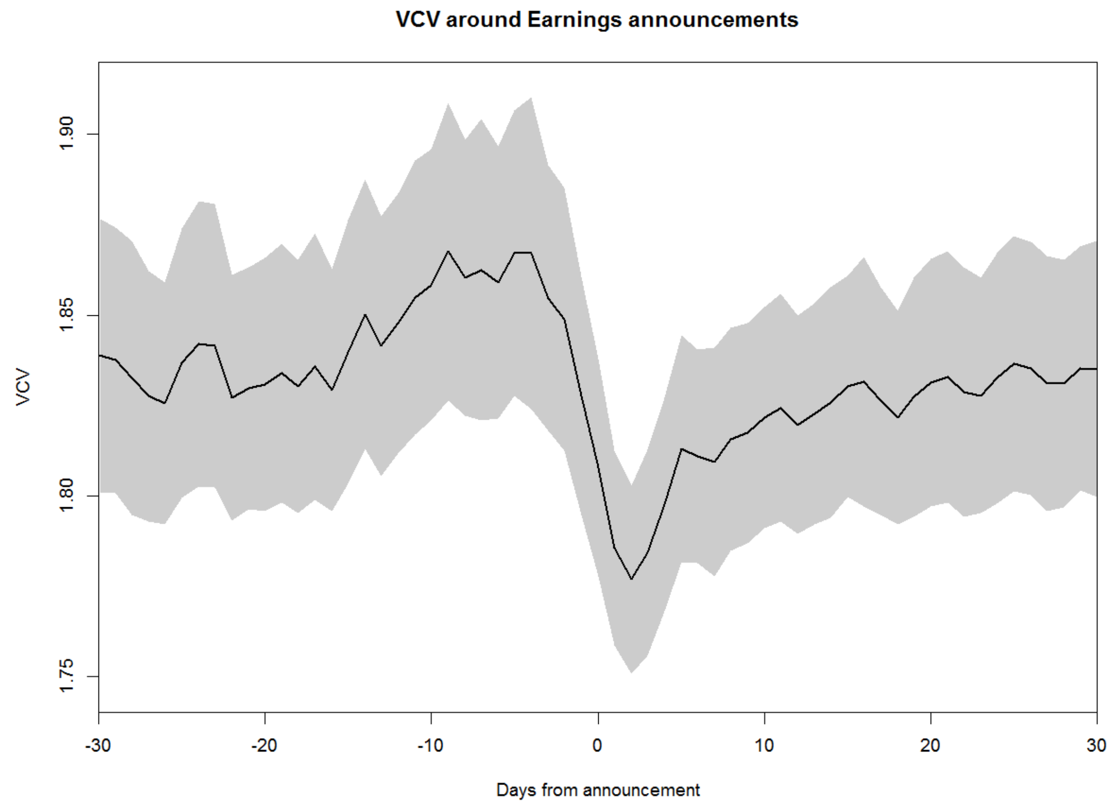

Figure 5: The black line shows the evolution of the daily cross-sectional VCV_{XS} around quarterly earnings announcements. The full sample includes all daily trading volumes over 61 days windows (day -30:30) around $N = 339,257$ quarterly announcements (sources: CRSP and COMPUSTAT). The reported VCV at d days after the announcement is estimated from the subsample of each stock's trading volume market shares at date d after each firm's announcement. The gray shaded areas indicate 95% confidence intervals: $VCV_{XS,d} \pm 1.96 \times S.E.(VCV_{XS,d})$. Standard errors ($S.E.$) are derived following Albrecher et al. (2010).

confidence bounds, computed from the asymptotic distribution of sample coefficients of variation as derived by Albrecher et al. (2010). Figure 4 clearly shows that VCV is higher in the weeks prior to the announcement, which could be due to uninformed investors delaying their trading activity when the announcement date is approaching. After information asymmetries are resolved on the announcement date, VCV is relatively low for multiple trading days. After 30 trading days, the cross-sectional VCV is approximately equal to the cross-sectional VCV 30 trading days prior to the announcement. In internet Appendix Figure B.1, we reproduce Figure 5 for various subsets of the data, showing a qualitatively similar pattern of VCV around earnings announcements for both NASDAQ and NYSE/AMEX stocks as well as before and after 2000.

Table 11: Volume around earnings announcements

This table reports the cross-sectional mean $\hat{\mu}_d$, standard deviation $\hat{\sigma}_d$ (both multiplied by 10,000), and coefficient of variation $VCV_{CS,d}$ of all firms' daily trading volume shares on day d before and after $N = 339,257$ firm-specific earnings announcement dates, as well as the difference between these moments d days before and after the announcement. *, ** and *** indicate significant differences at the 10%, 5%, and 1% level.

	$\hat{\mu}_d \times 10,000$				$\hat{\sigma}_d \times 10,000$				$VCV_{XS,d}$			
d	Before	After	Diff		Before	After	Diff		Before	After	Diff	
0	0.86	0.86	0.00		1.55	1.55	0.00		1.81	1.81	0.00	
1	0.81	0.87	0.06	***	1.47	1.55	0.08	***	1.83	1.78	-0.04	**
2	0.75	0.86	0.11	***	1.39	1.52	0.13	***	1.85	1.77	-0.07	***
3	0.74	0.83	0.10	***	1.37	1.49	0.12	***	1.85	1.78	-0.07	***
4	0.73	0.82	0.09	***	1.36	1.46	0.11	***	1.87	1.80	-0.07	***
5	0.73	0.80	0.07	***	1.36	1.46	0.09	***	1.86	1.81	-0.05	**
6	0.73	0.79	0.06	***	1.36	1.43	0.07	***	1.86	1.81	-0.05	**
7	0.73	0.79	0.06	***	1.37	1.43	0.06	***	1.86	1.81	-0.05	**
8	0.74	0.79	0.05	***	1.37	1.43	0.06	***	1.86	1.81	-0.05	*
9	0.74	0.78	0.05	***	1.38	1.42	0.05	***	1.87	1.81	-0.05	**
10	0.74	0.78	0.03	***	1.38	1.42	0.04	***	1.86	1.82	-0.04	
11	0.75	0.78	0.02	***	1.39	1.41	0.02	***	1.85	1.82	-0.03	
12	0.75	0.78	0.02	***	1.39	1.41	0.02	***	1.85	1.82	-0.03	
13	0.75	0.77	0.02	***	1.39	1.41	0.02	***	1.84	1.82	-0.02	
14	0.76	0.77	0.02	***	1.40	1.41	0.01	***	1.85	1.82	-0.02	
15	0.76	0.77	0.01	*	1.40	1.41	0.01	**	1.84	1.83	-0.01	
16	0.76	0.77	0.01		1.39	1.40	0.01	***	1.83	1.83	0.00	
17	0.77	0.77	0.00		1.40	1.40	0.00		1.83	1.82	-0.01	
18	0.77	0.77	0.00		1.40	1.40	-0.00		1.83	1.82	-0.01	
19	0.77	0.77	0.00		1.40	1.40	-0.00		1.83	1.83	-0.01	
20	0.77	0.77	-0.00		1.40	1.40	-0.00		1.83	1.83	0.00	
21	0.77	0.77	-0.00		1.41	1.41	-0.00		1.83	1.83	0.00	
22	0.77	0.77	0.01	*	1.40	1.41	0.01	**	1.83	1.83	0.00	
23	0.77	0.77	0.00		1.41	1.41	-0.00		1.84	1.83	-0.01	
24	0.77	0.77	0.00		1.41	1.41	-0.00		1.84	1.83	-0.01	
25	0.77	0.77	0.00		1.41	1.41	0.00		1.83	1.83	-0.00	
26	0.77	0.77	0.00		1.40	1.41	0.01	*	1.82	1.83	0.01	
27	0.77	0.77	0.00		1.40	1.41	0.01	**	1.83	1.83	0.00	
28	0.77	0.77	0.00		1.41	1.41	0.00	*	1.83	1.83	-0.00	
29	0.77	0.77	0.00		1.41	1.41	0.00		1.84	1.83	-0.00	
30	0.77	0.77	-0.00		1.42	1.41	-0.01	*	1.84	1.83	-0.00	

Table 11 reports the components of VCV: the cross-sectional mean and standard deviation of volume shares for each day around the announcement. The level of volume is low prior to announcements and high following announcement, which is consistent with the patterns documented by Chae (2005) and Akbas (2016). The standard deviation of volume moves in the same direction as the mean, which could be due to be the increased illiquidity and price elasticity in the days before the announcement, as documented by George et al. (1994) and Chae (2005). What we are most interested in is the pattern of VCV as a proxy for information asymmetry. Since the changes in the standard deviation are smaller in relative terms than the changes in the mean, VCV is high prior to the announcement and low afterwards. As Table 11 shows, the differences between VCV are statistically significant up to nine days up to nine days before and after the announcement.

This pattern of VCV around earnings announcements is consistent with the premise that information asymmetries are resolved around earnings announcements, and with the behavior of alternative information asymmetry measures. Johnson and So (2018) document that the Multimarket Information Asymmetry (MIA) measure, calculated from the relative trading volume of options and stocks, increases in the days before earnings announcements, and rapidly declines around the announcement, similar to VCV. Also Chordia et al. (2017) find that the volatility of order flow, driven by correlated liquidity demand, significantly increases before earnings announcements. There is mixed evidence on the behavior of PIN around announcement dates. Benos and Jochec (2007) and Duarte et al. (2017) find that PIN is in fact lower prior to earnings announcements and higher afterwards. Duarte et al. (2017) explain this puzzling result by showing that the PIN measure mis-identifies asymmetric information when applied on a daily frequency, and instead simply indicates abnormal turnover. Easley et al. (2008), on the other hand, estimate a generalized PIN model in which the arrival rate of information is time-varying and find that PIN is high (low) before (after) earnings announcements, resembling the pattern of VCV in Figure 5.

6 Conclusion

In this paper, we use the Kyle (1985) model to demonstrate that the distribution of total observed trading volume depends on the proportion of informed (correlated) liquidity seeking demand. Specifically, we show that the Volume Coefficient of Variation (VCV) increases in the proportion on informed trade. We therefore propose VCV as a measure of information asymmetry. Monte Carlo simulations confirm that VCV increases in the proportion of informed liquidity seekers, for a wide selection of model specifications.

Our empirical results indicate that stocks with high VCVs tend to have characteristics that are typically associated with asymmetric information (e.g.: high PIN, low breadth of institutional ownership, low analyst coverage, small size, low liquidity) and vice versa. Consistent with the hypothesis that informed trade is predictive of future price changes, we find that short-term return reversals are weaker for high VCV stocks, confirming that VCV is not just a measure of illiquidity. Our finding that VCV significantly increases following exogenous reductions in analyst overage due to brokerage closures, provides further evidence that VCV captures information asymmetry.

We introduce the cross-sectional VCV, which can be applied to evaluate information asymmetry in event time, e.g. following regulatory changes or other information events. We apply this measure to quarterly earnings announcements and find, consistent with prior research, that asymmetric information is higher shortly before the announcement, and lower afterwards.

Collectively, our empirical results provide broad support for the hypothesis that VCV is a measure of informed trading not only within our stylized microstructure model, but also when applied to observational data. Moreover, as we report in our internet appendix, all empirical results are qualitatively similar for subsamples of NYSE/AMEX and NASDAQ stocks, as well as for pre- and post-2000 periods, validating the robustness of VCV as a measure of information asymmetry in different market environments.

VCV is an appealing proxy for information asymmetry because of its simplicity: computing VCV, by dividing the sample standard deviation of daily trading volumes over the sample mean, is very straightforward. Unlike alternative measures of information asymmetry, estimating VCV requires only total trading volumes, as opposed to intraday transaction-level data. The measure is therefore applicable to any security for which trading volume is observable and can be implemented both in cross-sections and in time-series. The potential applications of our measure are numerous. For example, VCV can be used as a control variable in empirical corporate finance research when there is a need to control for information asymmetry, as a sorting characteristic in empirical asset pricing when studying the pricing effects of asymmetric information, or as the dependent variable of interest to compare information asymmetry across firms, countries, asset classes, or over time.

Appendix A: Variance of trading volume

Th first part of this appendix derives the variance of trading volume (Eq.5). The second part derives the variance of trading volume for the (m,n) model given in Proposition 2.

Define $Y_{MM} = |\sum_M y_i|$ as the part of double-counted volume traded by liquidity providers (the order imbalance), $Y_I = \sum_{1 \dots \eta M} |y_i|$ as the part traded by informed liquidity seekers and $Y_U = \sum_{\eta M+1 \dots M} |y_i|$ as the part traded by uninformed liquidity seekers. Then Eq.(1) can be rewritten as:

$$V = \tfrac{1}{2}\left(Y_I + Y_U + Y_{MM}\right). \tag{23}$$

The variance of double-counted trading volume is given by:

$$\begin{aligned} Var\left(2V\right) &= Var\left(Y_I\right) + Var\left(Y_U\right) + Var\left(Y_{MM}\right) \\ &\quad +2Cov\left(Y_I, Y_U\right) + 2Cov\left(Y_I, Y_{MM}\right) + 2Cov\left(Y_U, Y_{MM}\right). \end{aligned} \tag{24}$$

Using the properties of the Half Normal distribution, we find that:

$$\begin{aligned} Var\left(Y_I\right) &= \eta^2 M^2 \sigma^2 \left(1 - \tfrac{2}{\pi}\right) \\ Var\left(Y_U\right) &= (1-\eta) M \sigma^2 \left(1 - \tfrac{2}{\pi}\right) \\ Var\left(Y_{MM}\right) &= \left(\eta^2 M^2 + (1-\eta) M\right) \sigma^2 \left(1 - \tfrac{2}{\pi}\right). \end{aligned} \tag{25}$$

$Cov\left(Y_I, Y_U\right) = 0$, because the demands of informed and uninformed liquidity seekers are independent. Moreover, when M is large and $\eta > 0$, the order imbalance consists mainly of orders submitted by informed liquidity seekers. The orders of uninformed traders tend to net out against each other because of the *i.i.d* property. This implies that in the limit ($M \to \infty$), the liquidity suppliers trade exclusively to offset the imbalance from informed seekers. Therefore, $\lim_{M\to\infty} Cor\left(Y_U, Y_{MM}\right) = 0$ and $\lim_{M\to\infty} Cor\left(Y_I, Y_{MM}\right) = 1$. Given these correlations, Eq.(24) implies that when $M \to \infty$:

$$Var\left(\tfrac{2V}{M}\right) = Var\left(\tfrac{Y_I}{M}\right) + Var\left(\tfrac{Y_U}{M}\right) + Var\left(\tfrac{Y_{MM}}{M}\right) + 2\sqrt{Var\left(\tfrac{Y_I}{M}\right) Var\left(\tfrac{Y_{MM}}{M}\right)}, \tag{26}$$

which, given the variances in Eq.(25), results in:

$$
\begin{aligned}
Var\left(\tfrac{2V}{M}\right) &= \eta^2\sigma^2\left(1-\tfrac{2}{\pi}\right)+(1-\eta)M^{-1}\sigma^2\left(1-\tfrac{2}{\pi}\right)+\left(\eta^2+(1-\eta)M^{-1}\right)\sigma^2\left(1-\tfrac{2}{\pi}\right)\\
&\quad +2\sqrt{\eta^2\sigma^2\left(1-\tfrac{2}{\pi}\right)}\sqrt{\left(\eta^2+(1-\eta)M^{-1}\right)\sigma^2\left(1-\tfrac{2}{\pi}\right)}\\
&= 2\sigma^2\left(1-\tfrac{2}{\pi}\right)\left(\eta^2+(1-\eta)M^{-1}+\eta\sqrt{\eta^2+(1-\eta)M^{-1}}\right)\\
&= 4\sigma^2\left(1-\tfrac{2}{\pi}\right)\eta^2,
\end{aligned}
\tag{27}
$$

where the last step follows from $M^{-1}\to 0$ for large M. The standard deviation of trading volume divided by M thus equals to $\sigma\eta\sqrt{1-\frac{2}{\pi}}$, from which Proposition 1 is easily derived:

$$
\lim_{M\to\infty}\frac{s.d.(V)}{E\left[V\right]}=\lim_{M\to\infty}\frac{s.d.(V/M)}{E\left[V/M\right]}=\sqrt{2\pi-4}\frac{\eta}{\eta+1}. \tag{28}
$$

Proof of Proposition 2

The expected volume of trading volume is found by applying the properties of the Half-Normal distribution, given that u_i, x_j and $(\sum_n u_i+\sum_m x_j)$ all follow a Normal distribution around zero. To evaluate the variance of the trading volume we use the following lemma:

Lemma: If r and s are two i.i.d. random variables from the Standard Normal distribution, and α is a positive scalar, we have:

$$
Cov(|r|,|r+\alpha s|)=4\int_0^\infty r^2\Phi(\frac{r}{\alpha})\phi(r)dr+\frac{2\alpha^3-2(\alpha^2+1)^{\frac{3}{2}}}{(\alpha^2+1)\pi}-1, \tag{29}
$$

Where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density function and cumulative density function of the Standard Normal distribution.

Proof:

$$
\begin{aligned}
Cov(|r|,|r+\alpha s|) &= E[|r||r+\alpha s|]-E[|r|]E[|r+\alpha s|]\\
&= E[|r||r+\alpha s|]-\tfrac{2}{\pi}\sqrt{1+\alpha^2}.
\end{aligned}
\tag{30}
$$

We evaluate the first term by integration:

$$
\begin{aligned}
E[|r||r+\alpha s|] &= \iint |r(r+\alpha s)|d\phi(r)d\phi(s) \\
&= \int_{-\infty}^{0} (\int_{-\infty}^{-\frac{r}{\alpha}} (r^2+\alpha rs)\phi(s)ds + \int_{-\frac{r}{\alpha}}^{\infty} (-r^2-\alpha rs)\phi(s)ds)dr \\
&\quad + \int_{0}^{\infty} (\int_{-\infty}^{-\frac{r}{\alpha}} (-r^2-\alpha rs)\phi(s)ds + \int_{-\frac{r}{\alpha}}^{\infty} (r^2+\alpha rs)\phi(s)ds)\phi(r)dr \\
&= \int_{-\infty}^{0} (r^2\Phi(-\tfrac{r}{\alpha}) - \tfrac{\alpha r}{\sqrt{2\pi}}e^{-\frac{r^2}{2\alpha^2}} - r^2(1-\Phi(-\tfrac{r}{\alpha})) - \tfrac{\alpha r}{\sqrt{2\pi}}e^{-\frac{r^2}{2\alpha^2}})\phi(r)dr \\
&\quad + \int_{0}^{\infty} (-x^2\Phi(-\tfrac{r}{\alpha}) + \tfrac{\alpha r}{\sqrt{2\pi}}e^{-\frac{r^2}{2\alpha^2}} + r^2(1-\Phi(-\tfrac{r}{\alpha})) + \tfrac{\alpha r}{\sqrt{2\pi}}e^{-\frac{r^2}{2\alpha^2}})\phi(r)dr \\
&= 2\int_{-\infty}^{0} r^2\Phi(-\tfrac{r}{\alpha})\phi(r)dr - \int_{-\infty}^{0} r^2\phi(r)dr - \tfrac{2\alpha}{2\pi}\int_{-\infty}^{0} re^{-\frac{r^2}{2\alpha^2}-\frac{r^2}{2}}dr \\
&\quad -2\int_{0}^{\infty} r^2\Phi(-\tfrac{r}{\alpha})\phi(r)dr + \int_{0}^{\infty} r^2\phi(r)dr + \tfrac{2\alpha}{2\pi}\int_{0}^{\infty} re^{-\frac{r^2}{2\alpha^2}-\frac{r^2}{2}}dr \\
&= 2\int_{0}^{\infty} r^2\Phi(\tfrac{r}{\alpha})\phi(r)dr - \tfrac{1}{2} + \tfrac{\alpha^3}{(\alpha^2+1)\pi} \\
&\quad -2\int_{0}^{\infty} r^2(1-\Phi(\tfrac{r}{\alpha}))\phi(r)dr + \tfrac{1}{2} + \tfrac{\alpha^3}{(\alpha^2+1)\pi} \\
&= 4\int_{0}^{\infty} r^2\Phi(\tfrac{r}{\alpha})\phi(r)dr + \tfrac{2\alpha^3}{(\alpha^2+1)\pi} - 2\int_{0}^{\infty} r^2\phi(r)dr \\
&= 4\int_{0}^{\infty} r^2\Phi(\tfrac{r}{\alpha})\phi(r)dr + \tfrac{2\alpha^3}{(\alpha^2+1)\pi} - 1.
\end{aligned} \tag{31}
$$

Substitute (31) into (30) to obtain the lemma (29).

To evaluate the variance of the trading volume we use:

$$
\begin{aligned}
Var(2V) &= \sum_n var(|u_i|) + var(|\sum_m x_j|) + var(|z|) \\
&\quad +2Cov(|\sum_m x_j|,|z|) + 2\sum_n Cov(|u_i|,|z|),
\end{aligned} \tag{32}
$$

where $z = \sum_m x_i + \sum_n u_i$. Note that we can consider the total informed demand, $x \equiv \sum_m x_j = m\beta v = \sqrt{mn}\frac{\sigma_u}{\sigma_v}v$ as a single random variable. Using again the properties of the Half-Normal distribution, we find that the variance terms are:

$$
\begin{aligned}
\sum_n Var(|u_i|) + Var(|x|) + Var(|z|) &= n\sigma_u^2(1-\tfrac{2}{\pi}) + mn\sigma_u^2(1-\tfrac{2}{\pi}) \\
&\quad +(1+m)n\sigma_u^2(1-\tfrac{2}{\pi}) \\
&= 2(m+1)n\sigma_u^2(1-\tfrac{2}{\pi}).
\end{aligned} \tag{33}
$$

The first covariance term in (32) can be evaluated as follows:

$$Cov(|\sum_m x_j|, |z|) = Cov(|x|, |x+u|), \tag{34}$$

where $x \equiv \sum_m x_j \sim N(0, mn\sigma_u^2)$ and $u \equiv \sum_n u_i \sim N(0, n\sigma_u^2)$, and x and u are independent. From the Lemma, it follows that:

$$Cov(|x|, |x+u|) = mn\sigma_u^2(4\int_0^\infty x^2\Phi(\sqrt{m}x)\phi(x)dx + \frac{2(1-(m+1)^{\frac{3}{2}})}{\pi\sqrt{m}(m+1)} - 1). \tag{35}$$

The final covariance terms in (32) are all identical, and can be evaluated as:

$$Cov(|u_i|, |z|) = Cov(|u_i|, |u_i + z_{-i}|), \tag{36}$$

where $u_i \sim N(0, \sigma_u^2)$ and $z_{-i} \equiv \sum_{n|i} u_j + x \sim N(0, (n-1+mn)\sigma_u^2)$ are two *i.i.d.* Normally distributed random variables. From the Lemma, it then follows that:

$$\begin{aligned} Cov(|u_i|, |z|) \quad = \quad & \sigma_u^2(4\int_0^\infty x^2\Phi(\tfrac{x}{\sqrt{mn+n-1}})\phi(x)dx \\ & + \tfrac{2(mn+n-1)^{\frac{3}{2}} - 2(mn+n)^{\frac{3}{2}}}{\pi(mn+n)} - 1). \end{aligned} \tag{37}$$

Combining the variance terms (33), and the covariance terms (35) and (37) gives, after re-arranging, the variance of trading volume ($Var(V)$) as given in Proposition 2.

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