How (Un)Informed Is Trading?

Eric K. Kelley and Paul C. Tetlock*

May 2012

Abstract

We estimate a structural model of strategic trader behavior that sheds light on the determinants of trading volume and stock returns. Our novel identification approach exploits enormous empirical variation in trading and volatility associated with the time of day and public news arrival. Over 95% of trading occurs during regular market hours (9:30am to 4pm), even though prices exhibit considerable volatility during extended hours, especially when news arrives. For the model to explain the data, discretionary liquidity trading must constitute the bulk of trading volume and must increase significantly after news arrives. However, from 2001 to 2010, informed trading increasingly contributes to volume and stock price discovery because our estimate of the cost of acquiring private information falls by a factor of 12 in this decade.

---

* University of Arizona, ekelley@eller.arizona.edu and Columbia University, paul.tetlock@columbia.edu. An earlier version of this paper circulated under the title "Round-the-Clock News, Trading, and Returns." We thank Lauren Cohen, Rick Sias, and seminar participants at Arizona, Columbia, Georgia, and Tennessee for helpful discussions and Dow Jones for providing the news data used in this study.

DeBondt and Thaler (1995) argue that the high trading volume observed in financial markets "is perhaps the single most embarrassing fact to the standard finance paradigm." Since then, Chordia, Roll, and Subrahmanyam (2011) show that turnover in US markets has actually *increased* fivefold, implying annual volume is now *tens of trillions* of dollars. Although they argue that informed trading drives the recent trend, a complete characterization of traders' motives remains elusive. This paper attempts to fill this void by estimating a structural model with strategic informed and uninformed traders. The model sheds light on the determinants of trading volume and the relative importance of private and public information in price discovery.

In our model, as in Admati and Pfleiderer (1988), both informed and (uninformed) "liquidity" traders optimally choose to trade when others are trading because such clustering behavior minimizes traders' impact on prices. As in standard models, informed traders choose to enter by weighing the cost of acquiring and acting on information (c parameter) against their expected trading profits. The novel feature is that we allow liquidity traders' net benefits of learning and acting on their trading needs (h parameter) to vary with the time of day and the occurrence of news. This parameterization captures variation in traders' awareness of data, portfolio monitoring costs, rebalancing needs, and opportunity costs. Such variation causes trader attention to the market, and thus trading volume, volatility, and liquidity, to fluctuate as well.

To identify the model parameters, we exploit enormous empirical variation in trading and volatility associated with the time of day and news arrival in the electronic trading era. This study is the first to adopt this promising approach. Since 2000, revolutions in information and trading technology have enabled virtually round-the-clock market-related activity in US stocks. Newswires now arrive continuously throughout the day. Electronic communication networks give any institution or retail trader with a brokerage account the ability to trade outside regular market hours (from 9:30am to 4pm). Despite having this ability, few choose to trade in extended hours. Less than 5% of total trading in our sample takes place in the pre-market (7am to 9:30am in our study) and the after-market (4pm to 6:30pm). In contrast, stock return volatility during extended hours periods is more than half of that during the regular market. In fact, in periods when news arrives, extended hours volatility is on par with regular hours volatility.

We use these strong contemporaneous relationships between volume, volatility, and news arrival in each intraday period to estimate our structural model's parameters. Our estimates of the parameter (h) designed to measure time-varying trader attention to the market are highest during regular trading hours and trading periods soon after news arrives, which accords with intuition. In the model, these high h values motivate liquidity traders to enter the market and indirectly spur informed traders to enter by increasing their expected profits. Our estimates of the parameter (c) designed to measure the cost of acquiring private information are low enough so that dozens of informed traders choose to acquire information and trade during the regular market, but sufficiently high so that few opt to participate during extended hours sessions. When news occurs, more informed traders choose to enter because more liquidity traders enter the market and increase liquidity.

For the model to explain the data, liquidity trading must account for the bulk of trading activity, particularly during regular market hours. The central reason is that compared to extended hours periods, the level of trading volume is quite high in relation to volatility, suggesting non-informational trading is important. Our parameter estimates imply that non-informational trading accounts for about 95% of regular market volume in 2001-2005, though it declines to 85% in 2006-2010. This modest decline is matched by an increase in informed trading: from 3.6% to 11.4% of volume in the regular period. In large cap stocks (with size over

$10B), informed trading accounts for much more of regular, pre-, and after-market trading (18%, 41%, and 37%, respectively). These patterns are consistent with the qualitative findings in Chordia, Roll, and Subrahmanyam (2011) who analyze how empirical proxies for informed trading vary over time and across firms.

Our estimates indicate that dramatic changes in the information cost parameter (c) explain these patterns in informed trading. Whereas the attention parameter (h) is quite stable over time, information costs fall by a factor of 12 in the past decade. The decline in c is most pronounced for large cap stocks, where it falls by a factor of 30. These estimates are consistent with the theory that the widespread adoption of new information gathering and trading technologies has transformed trading, especially in large stocks.

The stark reduction in the cost of acquiring information has important implications for price discovery, too. In 2001 to 2005, private information revealed through trading explains just 8% of the variance in returns during the regular market, whereas it explains 76% of variance from 2006 to 2010. This change is again most stark for large cap stocks, though it pervades small caps (under $1B) and mid caps (between $1B and $10B) as well. These results arise because it is far less costly to gather and trade on value-relevant information in the later time period. By the time this information is publicly observable, most of it is already incorporated in prices. As a result, we find that the role of public information in price discovery has diminished over time.

Next we test our model's predictions for how prices and volume will respond in periods *after* news arrival. In the model, to mimic the 24-hour news cycle, we assume news affects business activities and awareness of data (h) for one full trading day. We find that this simple model correctly predicts the price response to news is immediate whereas the volume response can be delayed. Intuitively, because prices respond to information while volume arises primarily from non-informational motives, the two need not coincide.[1] For example, when public news arrives during the after-market period, price responds immediately, but the bulk of abnormal trading occurs during the regular market on the following trading day. The delayed and prolonged trading after news contrasts with the timing in models that generate trading mainly through differences in beliefs, such as those based on pre-event or event-period information (*e.g.*, Kim and Verrecchia (1991, 1994, and 1997)) or those based purely on differences in opinion (*e.g.*, Harris and Raviv (1993), Kandel and Pearson (1995), and Banerjee and Kremer (2010)). Such models make the counterfactual prediction that the impacts of news on volume and volatility coincide because both are caused by changes in investors' beliefs.

We further distinguish our model of liquidity trading from belief-based models of trading by investigating market activity around news events sorted on the basis of changes in analysts' beliefs about quarterly earnings. We separately consider news events in which analyst forecast dispersion decreases, remains similar, and increases within one week after the news. Although news events in which dispersion either increases or decreases are associated with the highest return volatility, such events are actually associated with slightly *lower* trading activity. This lack of trading when beliefs change appears inconsistent with the disagreement models of trading volume, but it can be reconciled with models of discretionary liquidity traders. Such traders may expect their trades to have more impact on prices when news has greater impact on the belief distribution, thereby deterring them from entering the market and trading.

We organize the paper as follows. Section 1 reviews the relevant literature. Section 2 presents the structural model of market activity and explains which empirical moments identify

[1] These predictions are not mechanically generated by the fact that we allow trader attention to vary with news. We also estimate a version of our model in which news does not affect attention but it does affect the extent of acquirable private information. This version makes nearly identical equilibrium predictions: volume after news again arises primarily from discretionary liquidity traders, who in this case choose to enter because news reduces information asymmetry and lowers their trading costs.

the key model parameters. Section 3 describes how we apply the model to the empirical data. It also describes the features of our databases on trading activity and news and provides summary statistics of the key moments. Section 4 presents our estimates of the model parameters, along with estimates of two alternative parameterizations. Section 5 analyzes decompositions of return variance and trading volume under the main parameterization. Section 6 tests the distinct predictions of the discretionary liquidity trader model and belief-based models of trading. Section 7 concludes and suggests directions for future research.

1. Literature Review

In this section, we briefly review three strands of literature: the determinants of trading volume, the roles of private and public information in stock price formation, and the extended hours markets. Readers with knowledge of these areas may prefer to skip this section.

A. Determinants of Trading

Classic models such as Milgrom and Stokey (1982) and Kyle (1985) consider two motives for trading: information and liquidity, where liquidity is simply an exogenous demand to transact for some reason other than information. While these models form the basis for most theory and intuition in market microstructure, they do not explain important stylized facts such as the tendency of trading to cluster near the beginning and ending of trading periods (Jain and Joh, 1986) or following information releases such as earnings announcements (Beaver, 1968). In light of this, Admati and Pfleiderer (1988) introduce *discretionary* liquidity traders who endogenously choose when to trade with the goal of minimizing their expected trading losses. To minimize the price impact of trading, each uninformed trader prefers to trade when other uninformed traders choose to enter the market, leading to clustering in trading volume.

In most other theories, changes in traders' relative beliefs cause trading around information releases. Kim and Verrecchia (1991) introduce a model in which a public signal resolves trader disagreement initially caused by noisy private signals about firm value. In contrast, Kim and Verrecchia (1994) model public signals that generate new private information and thus disagreement. Kim and Verrecchia (1997) allow for both types of public signals—that resolve or generate disagreement—and show that both can generate trading. Harris and Raviv (1993) offer an alternative model in which traders have different opinions about the impact of a public signal, which causes trading when the signal is informative. Similarly, Kandel and Pearson (1995) model volume that occurs when traders update their estimates of firm value using different likelihood functions, motivated by different prior beliefs. A recent model by Banerjee and Kremer (2010) presents a simple characterization of volume in differences in opinion models as resulting from changes in the level of investor disagreement.

Empirical work attributes most of the increase in trading volume in US stocks from $3.5 trillion in 1994 to $32.0 trillion in 2010 to institutional trading, which is often perceived as informed (Chordia et al. (2011)). There is also some support for the numerous theories based on information or differences in opinion in conjunction with information releases (see Bamber, Barron, and Stevens, 2011 for a thorough review). However, the notion of discretionary liquidity traders emphasized in our model has received almost no attention in the empirical literature. One notable exception is Kross, Ha, and Heflin (1994) who find that absolute change in beta around earnings announcements is positively related to announcement-period trading and attribute this trading to portfolio rebalancing, a specific type of discretionary liquidity trading. A second is

Chae (2005), who finds that trading volume declines before and then increases after scheduled earnings announcements. He interprets this pattern as discretionary liquidity traders postponing their orders until the information release resolves information asymmetry.

B. The Roles of Private and Public Information on Price Formation

Related research studies the roles of public and private information in price formation. French and Roll (1986) compare trading and non-trading periods and provide evidence that 86% of stock return variance is *not* caused by the arrival of public news and is *not* transitory. By process of elimination, one could infer that private information is the chief driver of price movements. Bolstering this view, evidence in Barclay, Litzenberger, and Warner (1990) and Ito, Lyons, and Melvin (1998) shows that hourly stock return variance is several times higher during trading hours, when informed trading can occur, as compared to non-trading hours. Taking a different approach, Roll (1988), Cutler, Poterba, and Summers (1989), Berry and Howe (1994), and Mitchell and Mulherin (1994) consider the volatility-news relationship. These studies complement the message of French and Roll (1986) by showing that public information arrival is only weakly linked to market activity.

In contrast, Jones, Kaul, and Lipson (1994) compare return variance during *endogenously determined* non-trading periods to variance when trading occurs. They find that a large proportion of variance occurs in the absence of trading, providing “evidence that public (versus private) information is the major source of short-term return volatility.” Ultimately, the relative importance of private and public information in market activity remains unknown both because these constructs are difficult to measure and because the world has changed dramatically since the initial studies. In the past 15 years, news production and trading volume have increased by an order of magnitude and return variance has risen sharply and fallen precipitously, as shown by Tetlock (2010), Chordia et al. (2011), and Brandt et al. (2009), respectively. Our model provides a simple variance decomposition into private and public information components that speaks directly to these issues.

C. The Extended Hours Markets

Finally, a small literature investigates extended hours markets, which many view as less liquid and important than the regular market. Barclay and Hendershott (2004) find that bid-ask spreads outside normal trading hours are about three or four times those during normal trading and attribute the difference to greater adverse selection. Barclay and Hendershott (2003) show that information asymmetry and price discovery per trade are highest during the pre-market.

Two other papers are more closely related to our work. Zdorovtsov (2004) finds that volatility in both extended and regular hours increases in the presence of public news. Jiang, Likitapiwat, and McInish (2011) report higher trading volume and lower quoted and effective spreads during extended hours periods containing earnings announcements than in periods without announcements. They also find that earnings announcement periods contribute more to 24-hour price changes than do non-announcement periods. We build on this literature by providing a comprehensive analysis of the relationship between volume, volatility, and news arrival during regular and extended trading hours in the context of a structural model.

2. Structural Model of Market Activity

A. Theory

Inspired by Admati and Pfleiderer (1988), we model prices and volume in a market for a single risky asset (hereafter "stock"), where liquidity traders and informed traders endogenously choose to participate. Each trading round in the model corresponds to an intraday period, such as the pre-market period. Because all traders choose whether to participate in each period, time variation in market activity can be rich even though there is effectively only one period in the model. The timing in each period is that public information arrives, traders choose whether to enter the market, private signals are realized, and trading occurs at a price set by the market maker.

The stock's value (F) at some distant future trading round T is given by:

$$F = \overline{F} + \sum_{t=1}^{T} d_t + \sum_{t=1}^{T} \varepsilon_t, \tag{1}$$

where $\overline{F}$ is the initial value of the stock in period 0, t indexes periods, and d_t and ε_t are independently distributed with means of zero and variances of σ_{dt}^2 and $\sigma_{\varepsilon t}^2$. In period t, both d_t and ε_t are revealed publicly. The key difference is that informed traders can acquire information about d_t one period in advance, whereas information about ε_t cannot be acquired. Thus, d_t and ε_t represent tractable and intractable information, respectively, in the sense of Mendelson and Tunca (2004). We assume that public news ($news_t \in \{0,1\}$) is the sole mechanism for releasing intractable information, implying that $\varepsilon_t = 0$ in non-news periods when $news_t = 0$.

In each period, each informed trader (i) chooses whether to enter the market based on whether her expected trading profits exceeds her information gathering and processing costs (c). By paying c, informed traders can observe d_{t+1}, which is normally distributed. Each informed trader is risk neutral and thus selects demand to maximize expected profits given her signal. The number of informed traders (m_t) is determined endogenously by free entry subject to a zero trading profit condition.

Each discretionary liquidity trader (j) enters the market if his expected benefit of rebalancing net of entry costs exceeds his expected trading losses. The main entry cost is the opportunity cost of time and attention required to monitor his portfolio exposures and determine his optimal trade (y_{jt}). If he enters the market, discretionary liquidity trader j buys y_{jt} shares, where y_{jt} is normally distributed with mean zero and variance σ_{yt}^2. We allow opportunity costs of time, attention, and rebalancing needs to vary across traders and summarize these considerations using a simple function h_t/j. This implies that liquidity traders (j) are indexed by their expected rebalancing benefit net of entry costs, which decrease from h_t to 0 as j increases. The number of discretionary liquidity traders (k_t) is determined endogenously by the free entry of liquidity traders who choose to participate. There are no non-discretionary liquidity traders, though liquidity traders with low j values exhibit strong desires to trade—especially when h_t is high.

News not only releases intractable information in the current intraday period, but it also may have longer-term impacts on trader attention and rebalancing needs, as captured by h_t. Motivated by the modern day 24-hour news cycle, we allow h_t to depend on whether news has arrived in the past 24 hours. Sequences of related news stories about a firm may unfold during a 24-hour period, bringing the news and the stock to the attention of more traders who may realize their current stock holdings differ significantly from their optimal allocation. Formally, we assume $h_t = h(RecentNews_t, t)$, where recent news is defined as:

$$RecentNews_t = 1-(1-news_t)(1-news_{t-1})(1-news_{t-2})(1-news_{t-3}). \qquad (2)$$

The risk neutral market maker only observes total order flow and thus cannot distinguish between orders from each trader. Assuming market making is competitive, the stock price is set such that the market maker’s expected profit is zero conditional on total order flow. We suppose further that the market maker's pricing function is linear in total order flow:

$$p_t = F_t + \lambda_t Q_t = F_t + \lambda_t(\sum x_{it} + \sum y_{jt}), \text{ where } F_t = \overline{F} + \sum_{s=1}^{t} d_s + \sum_{s=1}^{t} \varepsilon_s. \qquad (3)$$

In this equation, F_t represents expectation of F conditional on public information, λ_t is the sensitivity of price to net order flow (Q_t).

We solve the model by conjecturing an equilibrium and evaluating whether agents have an incentive to deviate using backward induction. We suppose that the m_t informed traders select their demands (x_{it}) to depend linearly on their signals, implying $x_{it} = \beta_t d_{t+1}$, where β_t measures trader aggressiveness. In the Appendix, we characterize the unique (symmetric) equilibrium in which informed traders and market makers follow the (same) linear strategies above and both informed and liquidity traders endogenously choose to participate in the market. The key endogenous parameters are the equilibrium sensitivity of prices to order flow (λ_t), trader aggressiveness (β_t), and the number of informed (m_t) and liquidity traders (k_t):

$$\lambda_t = c^{-1}(h_t / c + 1)^{-2}\sigma_{dt+1}^2 \tag{4}$$

$$\beta_t = (h_t + c)\sigma_{dt+1}^{-2} \tag{5}$$

$$m_t = h_t / c \tag{6}$$

$$k_t = ch_t(h_t / c + 1)^2\sigma_{dt+1}^{-2}\sigma_{yt}^{-2}. \tag{7}$$

B. Empirically Identifying the Model

We identify the exogenous parameters in the model, σ_{dt}^2, $\sigma_{\varepsilon t}^2$, h_t, and c, using return variance ($Var(r_t)$) and average volume ($E(v_t)$) conditional on news ($news_t \in \{0,1\}$) in the four periods. We allow σ_{dt}^2 and $\sigma_{\varepsilon t}^2$ to vary only across the four intraday periods. Intuitively, return variances in news and non-news periods provide estimates of σ_{dt}^2 and $\sigma_{\varepsilon t}^2$, which are measures of tractable and intractable information. Examining volume in news and non-news periods allows us to isolate the changing net benefits of entry (h_t) for liquidity traders, as well as the cost (c) of informed traders acquiring information.

We compute simple returns (r_t) using:

$$r_t = p_t - p_{t-1} = \lambda_t Q_t - \lambda_{t-1}Q_{t-1} + d_t + \varepsilon_t. \tag{8}$$

The variance of returns is then:

$$
\begin{aligned}
Var(r_t) &= \sigma_{\varepsilon t}^2 + \lambda_t^2 Var(Q_t) + Var(d_t - \lambda_{t-1} Q_{t-1}) \\
&= \sigma_{\varepsilon t}^2 + (h_t / c)(h_t / c + 1)^{-1} \sigma_{dt+1}^2 + (h_{t-1} / c + 1)^{-1} \sigma_{dt}^2 .
\end{aligned} \tag{9}
$$

We define volume as in Admati and Pfleiderer (1988) using

$$
v = \max(\sum buys, \sum sells), \tag{10}
$$

where buys and sells are measured using quantities of shares. We can decompose expected volume into one half of the sum of buys and sells plus the absolute value of net buying by the market maker, which can be written as:

$$
\begin{aligned}
E(v_t) &= \frac{1}{2}(m_t \beta_t E[| d_{t+1} |] + k_t E[| y_{jt} |]) + \frac{1}{2} E[| m_t \beta_t d_{t+1} + \sum y_{jt} |] \\
&= \frac{h_t (h_t / c + 1)}{\sqrt{2\pi} \sigma_{dt+1}} \left[1 + (h_t + c) \sigma_{dt+1}^{-1} \sigma_y^{-1} + \sqrt{1 + c / h_t} \right].
\end{aligned} \tag{11}
$$

The first two terms in brackets come from trading between liquidity and informed traders and among liquidity traders, while the third term accounts for trades involving the market maker.

To eliminate confounding impacts of repeated news stories, we define each firm's first news event in a 24-hour period as $FirstNews_t = news_t (1 - news_{t-1})(1 - news_{t-2})(1 - news_{t-3})$. This means that $FirstNews_t = 1$ if $news_t = 1$ and there was no news in the prior three intraday periods. We compare firm return variance in situations where there is first news to that in situations where there has been no recent news. We use the variable subscript *nt* to denote periods *t* in which $FirstNews_t = RecentNews_t = n$. Thus, $Var(r_{1t})$ is the firm's return variance in periods *t* when the firm has first news (and thus recent news), whereas $Var(r_{0t})$ is return variance in periods when the firm has no recent news (and thus no first news). By varying the *n* and *t* subscripts, we separately measure return variance and trading volume depending on whether news occurs during the regular market, pre-market, overnight, and after-market periods. Hereafter, we refer to periods with $FirstNews_t = RecentNews_t = 1$ as news periods and those with $FirstNews_t = RecentNews_t = 0$ as non-news periods.

The lack of overnight trading activity has implications for the model parameters. Because overnight volume is zero, regardless of whether news occurs, overnight h_t is zero for news (h_{1t}) and non-news (h_{0t}) periods. Similarly, we assume that no tractable information is available overnight while no trading occurs. This implies that $\sigma_{dt}^2 = 0$ for the pre-market period (following the overnight period) when such tractable information would have become public.

After imposing these restrictions, we estimate the remaining 14 parameters: σ_{dt}^2 in the three trading periods, $\sigma_{\varepsilon t}^2$ in all four intraday periods, one c parameter, three h_{1t} parameters, and three h_{0t} parameters.[2] Fortunately, the four intraday return variance equations and three intraday expected trading volume equations for news and non-news periods ($Var(r_{1t})$, $Var(r_{0t})$, $E(v_{1t})$, and $E(v_{0t})$) provide 14 empirical moments that can be used to exactly identify the 14 parameters above. The next two sections describe the data and procedures used in this estimation.

3. Data and Empirical Moments

Our eligible sample spans 2001 to 2010 and includes NYSE, AMEX, and NASDAQ stocks. We pool intraday observations across similarly-sized firms each year in the sample and separately estimate the 14 moments described above for each intraday period (pre-market, regular hours, after-market, and overnight). Then we average across size groups and years to obtain a set of moments for each intraday period. This procedure mitigates measurement error resulting from firm-level estimates, assigns each size group and year equal weight, and allows us to analyze and control for differences across size groups. Throughout the paper, we compute standard errors based on 1,000 block bootstrap samples. The samples are stratified by year, where each year consists of 50 randomly drawn one-week blocks of return and volume data for

[2] Because the impact of news lasts for 24 hours, the values h_{1t} and h_{0t} not only denote the parameters in periods when $FirstNews_t = RecentNews_t = 1$ and $FirstNews_t = RecentNews_t = 0$, respectively, but they also characterize the parameter values in all periods when $RecentNews_t = 1$ and $RecentNews_t = 0$, regardless of whether first news occurs.

all firms and intraday periods in that week. The standard error is the standard deviation of the estimate of interest—*e.g.*, empirical moment or model parameter—across these 1,000 samples. This procedure assumes independence of returns and volume across weekly blocks of data, but it allows for arbitrary correlation of returns and volume at higher frequencies and across firms. The next subsection introduces the data on stock prices, trading volume, and news releases that forms the basis for the moment estimation.

A. Data

For the pre-market, regular market, and after-market, we obtain trade-by-trade price and volume data from the NYSE TAQ database.[3] We do not include any trades during the overnight period because few trades are reported for most of our sample period. We adjust for non-standard opening and closing times such that the regular trading period only includes the hours in which the market is open, and we consider weekends and weekdays in which the market is closed as part of the overnight period. As discussed in the Appendix, we employ several standard techniques from the microstructure literature to compute an accurate trade-based return for each intraday period. We adjust all firm returns for market returns by subtracting the contemporaneous intraday return of the SPDR S&P 500 ETF (SPY). We compute share turnover from each period as the market value of share volume scaled by market cap at the end of the prior calendar year.

We measure firm-specific news using the Dow Jones archive. These data include all DJ newswire and *Wall Street Journal* stories from 2001 to 2010. For each story, DJ provides stock codes indicating which firms are meaningfully mentioned and a timestamp indicating when the

[3] Barclay and Hendershott (2008) argue that extended hours trades and quotes are adequately represented in the TAQ database. See their section 2.1 for a detailed analysis.

story became publicly accessible. To focus on firm-specific news, we only consider stories that mention at most two publicly trades U.S. stocks. The variable $news_{it}$ equals one when news mentions firm i during intraday period t and zero otherwise. For small and mid cap (large cap) firms, we require at least one (two) story mention(s) to constitute news. This convention does not count isolated stories for large cap stocks as news because large firms frequently receive news coverage even when no new public information exists.

We employ additional sample filters based on size, news coverage, and extended hours trading activity from the prior calendar year. First, we retain only stocks having market capitalizations above \$100 million and share prices greater than \$1 at the end of the prior year. Second, we require a firm to have a news story in a minimum of four pre-market periods and four after-market periods. Third, firms must also have trading in at least 20 pre-market periods and 20 after-market periods. Finally, we divide the firms into three size subsamples based on market capitalization from the prior year-end. We define "large cap," "mid cap," and "small cap" stocks as those with market capitalizations within the intervals [\$10B,¸∞), [\$1B,\$10B), and [\$100M,\$1B), respectively. These size groups contain an average of 95, 245, and 237 firms per year, respectively.

B. Empirical Moments

For each of the four intraday periods, Table 1 and Figure 1 describe the probability of news arrival for the full sample and separately for each size group. Three general patterns are noteworthy. First, while the regular period has the highest probability of news, the majority of news stories occur in the other three periods. The unconditional probability of news in a regular period is about 0.15. The probabilities of news in the pre-market, overnight, and after-market periods are 0.10, 0.12, and 0.08, respectively. Furthermore, measured as an hourly arrival rate (not shown), the probability of news is actually highest during the pre-market and after-market periods. Second, regardless of the period, news occurs more frequently for large cap stocks than for mid or small caps. Third, as shown in Figure 1, the probability of news arrival in every intraday period increases substantially around 2003 and plateaus through 2010. These patterns generally hold for the variable $FirstNews_t$ (the probability of the first news occurrence in a 24-hour period) as well.

[Insert Table 1 here.]

[Insert Figure 1 here.]

Table 2 presents conditional return variance moments used in the estimation along with unconditional variances that serve as a benchmark. We account for spurious reversal due to transitory noise in the period price *t* by computing $Var(r_t)^* = Var(r_t) + Cov(r_t, r_{t-1}) + Cov(r_t, r_{t+1})$. Interestingly, this adjustment affects return variance by less than 15% in each intraday period, implying that microstructure noise is not too severe. To ease comparison across periods, we report hourly volatilities in percent by dividing each variance by the number of hours in the intraday period and then taking the square root.

[Insert Table 2 here.]

The upshot of Table 2 is that news is consistently associated with higher volatility—volatility conditional on *FirstNews*=1 always exceeds that conditional on *RecentNews=0*, and the difference is economically staggering. In the regular period, volatility on news days is about 130% of that on non-news days. In the pre-market, overnight, and after-market periods, this ratio is even higher at 293%, 200%, and 364%, respectively. Qualitatively similar patterns appear within each size group.

We also note that hourly volatility during extended trading hours is of a similar magnitude as that during regular trading, especially when comparing periods with news. This finding is surprising in light of earlier evidence from French and Roll (1986) that volatility when the regular market is open far exceeds volatility when the regular market is closed. Our results may differ from theirs because new technologies have changed the nature of trading and news dissemination.

Table 3 presents conditional volume moments for the pre-, regular, and after-market periods. Numbers in the table are hourly turnover expressed in basis points. Similar to the conditional variance results, there is far more trading in periods with news than in periods without news. For the regular, pre-, and after-market periods, respectively, turnover with news is 145%, 723%, and 688% of that without news. However, unlike the variance patterns, almost all trading takes place during regular market hours irrespective of the occurrence of news. These stark patterns in variance and trading volume are key to identifying the model in Section 2.

[Insert Table 3 here.]

We summarize the volatility and volume results over time in Figure 2. The four panels represent the intraday periods. The bars depict the difference in turnover during news and non-news periods, while the lines depict differences in volatility. This figure reveals that the positive associations between news arrival and volatility and between news arrival and volume are quite robust over time. In the next section, we estimate our structural model's exogenous parameters.

[Insert Figure 2 here.]

4. Estimates of the Model Parameters

A. Mapping the Model into the Data

To facilitate comparisons of empirical moments and parameter estimates across firms and over time, we defined scaled versions (denoted by *) of the moments and parameters in terms of each firm's shares outstanding (θ) and share price (p):

$$Var(r_t^*) = Var(r_t / p) \tag{12}$$

$$E(v_t^*) = E(v_t / \theta) \tag{13}$$

$$h_t^* = h_t / (p\theta) \tag{14}$$

$$c^* = c / (p\theta) \tag{15}$$

$$\sigma_{dt+1}^* = \sigma_{dt+1} / p \tag{16}$$

$$\sigma_{\varepsilon t}^* = \sigma_{\varepsilon t} / p \tag{17}$$

$$\sigma_y^* = \sigma_y / \theta \tag{18}$$

$$\lambda_t^* = \lambda_t \theta / p \tag{19}$$

$$\sigma_{rt}^* = \sigma_{rt} / p \tag{20}$$

With these definitions, one can verify that the equations expressing the parameter estimates in terms of the empirical moments remain virtually identical to the original equations in Section 3. The only differences are that simple returns become percentage returns, share volume becomes share turnover, and all parameters in the new equations have asterisks. For practical purposes, we measure shares outstanding and share price at the end of the previous period.[4] In what follows, model parameters are scaled as in Equations (12) to (20), but we suppress the asterisk superscripts to economize on notation.

To obtain a conservative estimate of the importance of liquidity trading, we set the volatility of each liquidity trader's demand (σ_y) equal to the maximum value subject to the constraint that at least one liquidity trader must trade in each period. At least one liquidity trader is necessary for the model to predict that trading will occur, which holds empirically in each period. This maximum value for liquidity trading size is approximately σ_y = 0.2 bps of firm value. In the smallest sample firms with market capitalizations of \$100M, this σ_y = 0.2 bps trade size corresponds to \$2,000, which is empirically reasonable for a single retail trade. In the largest firms with market capitalizations of \$100B, this implies a typical liquidity trade size of \$2M. One could interpret this large liquidity trade as either a single large institutional investor or as a

[4] Technically, this timing induces a tiny approximation error in the parameter estimates, but it is typically negligible because the average intraday gross return is very close to 1.0.

group of 100 perfectly correlated retail trades of $20,000 each.[5]

B. Parameter Estimates

We estimate the model using the efficient generalized method of moments (GMM). Specifically, we minimize the model's squared prediction errors for each moment using a weighting matrix equal to the inverse of the covariance matrix of the empirical moments. Hansen (1982) shows that this weighting scheme is efficient. As explained in Section 3, we obtain the 14 by 14 covariance matrix of the 14 empirical moments using a block bootstrap technique.

This efficient GMM procedure yields a solution for the 14 model parameters that *exactly* fits the 14 empirical moment equations. This demonstrates that our modeling assumptions do not impose any restrictions on parameters that are infeasible given the empirical moments.[6] Table 4 presents point estimates and standard errors for the key model parameters, h, c, σ_d, and $\sigma_{\varepsilon 1}$ ($\sigma_\varepsilon(news)$) for each of the four intraday periods. We compute the parameters' standard errors using the standard GMM formula based on the delta method—*i.e.*, using the moments' bootstrapped covariance matrix and the sensitivity of each moment to each parameter. Panel A shows the estimates for the full sample, while Panels B and C show results for the 2001 to 2005 and 2006 to 2010 periods. Panels D, E, and F present results for firms in the three size groups.

[Insert Table 4 here.]

Focusing on Panel A, one sees the estimated expected benefits of rebalancing net of entry costs (h values) range within an order of magnitude of $1 per $1 million in market capitalization. The estimated net benefit of entry is $1,000 for a typical $1B firm, which is in the range of

[5] If we use smaller σ_y values, we obtain results indicating that liquidity trading is more important than in our base case with σ_y = 0.2 bps.
[6] Technically, the model is over-identified if we also restrict each of the parameters to be non-negative. These overidentifying restrictions are satisfied even when we do not impose this restriction on the parameters.

plausible values for certainty equivalents of hedging needs and opportunity costs of time for wealthy investors. Comfortingly, this estimated $1,000 benefit from entry is considerably smaller than typical retail order sizes of $10,000 and is far smaller than common institutional order sizes. In addition, the estimated h value is the expected benefit of the first trader who would choose to enter, whereas the benefit for the j^{th} trader is only h/j, which is orders of magnitude lower than h if j is high. As discussed below, our parameter estimates imply that far more liquidity traders enter during the regular market period and in periods when news occurs.

The h parameter is dramatically higher during the regular market period, as compared to the pre- or after-market. This suggests either rebalancing is less necessary or market participation is more costly (lower h) during extended market hours—both of which are plausible. The values of investors' other asset holdings probably change most during normal business hours. Monitoring portfolio exposures and attending to the market is presumably more costly when the regular market is closed.

Both data accessibility and rebalancing needs can also help explain why h is higher in periods with news. By providing information about the stock and bringing attention to it, news lowers investors' costs of monitoring and evaluating the stock's suitability in their portfolios. If investors have not rebalanced their positions in a long time, their desired holdings may have changed since their last portfolio evaluation. In addition, news about a stock can affect its risk. Changes in a stock's idiosyncratic risk can affect investors' desired holdings if they hold non-market weights on the stock. Changes in systematic risk could affect investors' desired holdings if their other asset holdings are exposed to similar risks.

In contrast to the dramatic differences across intraday periods, the h parameters are remarkably stable over time, as shown in Panels B and C. Mechanically, this is somewhat surprising because higher h values (all else equal) are associated with more trading activity; and such activity has increased significantly over time. However, there is no economic reason to expect that traders' entry costs have increased, which is consistent with the fact that *h* estimates in Panel C are similar or lower than those in Panel B. Panels D, E, and F show that the *h* estimates across the size groups accord with intuition, too. For traders with large stakes, rebalancing needs measured as a fraction of firm value are likely to be greater in small firms. In addition, the difference between *h* in news and non-news periods is larger in small firms, which could happen because relevant data about small firms is less widely available.

The second key model parameter is the cost of acquiring private information (*c*), which is estimated to be approximately $2.13 per $1 million in market capitalization or 0.0213 bps of firm value. This value is plausible in light of the French (2008) estimate of the cost of active management as a percent of firm value, which is stable at roughly 67 bps per year or 0.27 bps per trading day. Comparing our cost of acquiring information about a firm in one intraday period to the French (2008) daily estimate for an entire portfolio, one would infer that the typical active portfolio manager acquires information about 13 firms (0.27 / 0.0213) in at least one intraday period, which is in the realm of plausibility.

A comparison of Panels B and C in Table 4 reveals that the cost of acquiring and trading on private information (*c*) fell by a factor of 12 (from $4.0*10^{-6}$ to $3.3*10^{-7}$) across the two 5-year samples. In the model, lowering *c* induces informed traders to enter and increases volume in all periods, though it affects regular market volume most. The reason is that the number of informed traders is highest in the regular market and such traders do not internalize their impacts of entering the market on existing traders' profits. More subtly, because entry by informed traders affects variance more when there are fewer informed traders, lowering *c* increases regular market variance relatively less than it increases variance in other periods. In the past decade of data, we observe a relative increase in regular market volume and a relative decrease in regular market variance, which corresponds to a reduction of *c* in the model. The observed overall decrease in variance across all periods in the past decade corresponds to an even larger reduction in *c*.

Panels D, E, and F show that the cost of acquiring information as a percentage of firm value is over 5 times lower for large firms ($9.1*10^{-7}$) than it is for small firms ($4.9*10^{-6}$). This makes sense if there is some fixed cost of acquiring information. In unreported results, we find that the cost of acquiring information declines even more sharply for large firms in the 2006 to 2010 period (from $2.2*10^{-6}$ to $7.4*10^{-8}$, a factor of 30). As a basis for comparison, a recent *Wall Street Journal* story provides a direct estimate of the cost of informed trading in large firms.[7] Several hedge funds paid up to $10,000 each to acquire private information about a December 8th, 2009 health care law that affected four large health care stocks. As in the model, the information was acquired during the regular market, one intraday period in advance of its release during the after-market period. Based on the cumulative market capitalization of the stocks (about $100B), the estimated model cost of $7.4*10^{-8}$ would imply that each hedge fund would need to pay $7,440, which is similar to the reported cost of the meeting.

Lastly, the model estimates the amounts of tractable (σ_d) and intractable information ($\sigma_{\varepsilon 1}$) to be of the same order of magnitude in the pre-, regular, and after-markets. It is somewhat surprising that similar price discovery occurs in these three intraday periods even though just 1% of trading activity takes place during extended market hours. We analyze this phenomenon further in Section 5 when we decompose return variance and volume. There we also discuss the general implications of all of our structural estimates for the nature of trading and the role of private and public information in price discovery.

---

[7] *Wall Street Journal*, December 20, 2011, “Inside Capital, Investor Access Yields Rich Tips” by Brody Mullins and Susan Pulliam.

C. Alternative Parameterization of the Model

This subsection demonstrates that the model's key parameters are not sensitive to two of our assumptions. First, we consider the impact of our preferred parameterization in which news affects trader attention (h) rather than the amount of tractable information (σ_d) that can be acquired. Here we estimate an alternative model in which news does not affect trader attention (h) but it does affect the extent of learnable private information (σ_d). In this alternative model, only the subscripts on σ_d and h in the predicted moment equations (9) and (11) change. As before, we estimate the model using efficient GMM and obtain an exact fit to the 14 empirical moments. Panel A in Table 5 presents the results of this estimation for the full sample.

[Insert Table 5 here.]

The main result in Table 5A is that the parameter estimates look very similar to those in Table 4A, implying both versions of the model make similar equilibrium predictions. Specifically, the estimates of h(*no news*) in Table 4A are nearly identical to the estimates of h in Table 5A; and the estimates of σ_d in Table 4A are nearly identical to the estimates of σ_d(*no news*) in Table 5A. The parameter estimates in Table 5A indicate that news reduces information asymmetry between traders by lowering tractable private information (σ_d(*news*) < σ_d(*no news*)).[8]

The economic explanations for trading around news are slightly different in the models in Tables 4A and 5A. In the model where h varies with news, discretionary liquidity traders choose to enter because either their direct costs of entry decrease or their rebalancing needs increase (h(*news*) > h(*no news*)). In the model where σ_d varies with news, discretionary liquidity traders choose to enter because news reduces information asymmetry (σ_d(*news*) < σ_d(*no news*)) and lowers their trading costs. However, in both models, the ultimate effect is that discretionary

[8] Tetlock (2010) studies return predictability around news and argues that news reduces information asymmetry.

liquidity traders enter in massive quantities around news, so most of the testable predictions of the two models are indistinguishable.[9]

Next, we consider the impact of our assumption that liquidity trading is independent across traders. We do this by increasing the assumed size of each liquidity trader (σ_y). This effectively increases the correlation among liquidity trades because each trader's demand is perfectly correlated with itself. We can increase the correlation in liquidity trading only in the regular market period because it is already near one in the extended hours periods when few traders choose to enter—*e.g.*, in the pre-market period without news, only one trader enters. Panel B in Table 5 presents estimates from the model in which the regular market trade size is now σ_y = 2 bps, while it remains at σ_y = 0.2 bps during extended hours.

Table 5B shows that this tenfold increase in liquidity trader size almost doubles implied liquidity needs (h), while reducing implied information costs (c) and the amount of tractable information (σ_d) by factors of 4 and 2. The main impact is that liquidity (informed) trading becomes a smaller (larger) component of overall trading. However, informed trading contributes less to price discovery because of the decline in tractable information. Despite these nontrivial quantitative changes, none of the qualitative statements in the forthcoming volume and variance decomposition would be affected by this increase in correlation. Moreover, a single liquidity trade of 2 bps of firm value is quite large, exceeding the typical trade size of an institutional portfolio transition, which Obhizhaeva (2009) estimates to be 1.5 bps. Such transitions represent unusually large liquidity-motivated trades and thus provide a reasonable upper bound. In fact, Obhizhaeva (2009) documents that only 19% of such trades is executed on the first day, suggesting that 0.19 * 1.5 bps = 0.29 bps is a more realistic trade size for a single day.

[9] In the model in Table 4, there is also some entry by informed traders around news, but we will see in Section 5 that this effect is small compared to the influx of non-informational traders around news.

5. Implications of the Model for Price Discovery and Trading Activity

A. Theoretical Volume and Variance Decompositions

The model in Section 2 allows one to analyze the relative contributions of informed and liquidity traders to market activity. To decompose trading volume, we separately consider the quantities of buy and sell orders that transact between traders and the net order flow (Q) in which market makers take the other side of the trade. We assign half the volume arising from a trade to each counterparty participating in the trade. Thus, the volume attributable to market makers (v_{Mt}) is half of the expected net order flow aggregated across both trader groups, which is:

$$E(v_{Mt}) = \frac{1}{2}E(|Q|) = \frac{\sqrt{ch_t}\,(h_t/c+1)^{3/2}}{2\sqrt{2\pi}\sigma_{dt+1}} \tag{21}$$

The trading volume attributable to each group of traders is then half of the sum of their buy orders and sell orders plus half of their proportion of trading with market makers. The proportion of variance in net order flow (Q) arising from informed traders is $h_t(h_t+c)^{-1}$. Expected trading volume arising from informed traders (v_I) is given by:

$$E(v_{It}) = \frac{h_t(h_t/c+1)}{\sqrt{2\pi}\sigma_{dt+1}}\left[1+\frac{1}{2}\frac{h_t}{h_t+c}\sqrt{1+c/h_t}\right], \tag{22}$$

where the first term reflects trades with liquidity traders and the second reflects trades with market makers. Lastly, the expected volume from liquidity traders (v_{Lt}) is:

$$E(v_{Lt}) = \frac{h_t(h_t/c+1)}{\sqrt{2\pi}\sigma_{dt+1}}\left[(h_t+c)\sigma_{dt+1}^{-1}\sigma_y^{-1}+\frac{1}{2}(h_t/c+1)^{-1}\sqrt{1+c/h_t}\right]. \tag{23}$$

The first term comes from trading among liquidity traders as well as between liquidity and informed traders, while the second term accounts for trading with the market maker. Because these three components equal total expected volume, we can express each as a fraction of the total using:

$$\frac{E(v_{It})}{E(v_t)} + \frac{E(v_{Lt})}{E(v_t)} + \frac{E(v_{Mt})}{E(v_t)} = 1. \tag{24}$$

This equation is the basis for the volume decompositions that we report.

We can also decompose return variance in Equation (9) into three components. We report variance decompositions in which each component is expressed as a fraction of the total variance as described below:

$$\frac{\sigma_{\varepsilon t}^2}{Var(r_t)} + \frac{h_t(h_t + c)^{-1}\sigma_{dt+1}^2}{Var(r_t)} + \frac{(h_{t-1}/c + 1)^{-1}\sigma_{dt}^2}{Var(r_t)} = 1. \tag{25}$$

The first term reflects intractable information, which only arrives in periods with public news. The second term represents price discovery arising from trading on private information. The third term measures the revelation of tractable information that the previous period's price did not fully reveal. This term comprises public information revealed by sources other than Dow Jones news, including softer information sources, such as social media, television, radio, and word of mouth.

B. Estimated Volume Decomposition

In Figures 3A to 3C, we report the decomposition of expected volume from Equation (24) for the regular market (3A), pre-market (3B), and after-market (3C) periods. Table 6 shows more detailed volume decompositions. The four panels represent the intraday periods, while the six rows in each panel indicate the sample used: full sample, two 5-year subperiods, and the three firm size groups. To construct the tables and figures, we substitute our parameter estimates for news and non-news periods from Table 4 into Equations (21) to (23), weighting the periods by the probability of news occurring in the past 24 hours.[10]

[Insert Figure 3 here.]

[10] Recall that the *h* parameter depends on whether news occurs in the past 24 hours.

[Insert Table 6 here.]

The most striking fact in the figures is that discretionary liquidity trading accounts for the vast majority of volume in each of the three intraday periods, especially in the regular market where it is 92% of volume. One can infer the importance of discretionary liquidity trading from the fact that regular market volatility is comparable to volatility in the other periods, whereas regular market volume is nearly 100 times higher. This implies that liquidity is high in the regular market, which motivates many liquidity traders seeking to minimize their price impact to enter the market. For the same reason, many informed traders enter the market and trade aggressively on their information. However, such intense trading reveals their information almost perfectly, which lowers informed trading profits and deters further entry. Because there is no such counterbalancing force stopping liquidity traders from entering, discretionary liquidity trading constitutes the lion's share of volume.

Subperiod analysis reveals the implications of the decline in the cost of acquiring information documented in Table 4. In the regular market, informed trading accounts for 3.6% of trading volume from 2001 to 2005 and 11.4% from 2006 to 2010. Although the percentage of informed trading volume appears low even in the more recent period, one must remember that total volume is $32 trillion in 2010. This implies that informed volume exceeds $3.5 trillion. While the percentage of informed volume is slightly higher at 25% in the pre- and after-market periods (from 2006 to 2010), the dollar amount of informed trading in these periods pales in comparison to the tens of trillions traded in the regular market.

C. Estimated Variance Decomposition

Figures 4A to 4D show the decomposition of return variance in Equation (25) for each of the four intraday periods, again based on the model parameters shown in Table 4. The last three columns in Table 6 report the variance decomposition results. The dramatic difference between the variance and volume decomposition results is that a large fraction of return variance comes from trading on private information, particularly in the second half of the sample. In the 2006 to 2010 period, 77% of return variance during the regular market comes from informed trading. The sharp decrease in information acquisition costs causes this increase in price discovery coming from informed trading.

[Insert Figure 4 here.]

A second notable finding is that the fraction of variance (*e.g.*, in the regular market) attributable to public news (7%) is far lower than the fraction of variance coming from the delayed public release of undiscovered tractable information (60%), shown in the second column of Table 6 labeled "other public." In the regular market, the difference between these two components of variance is largest (6% versus 86%) from 2001 to 2005, when high information acquisition costs deterred the collection of tractable information. In 2006 to 2010, when information acquisition costs fell by an order of magnitude, the difference narrowed to 7% versus 16%. Only in the after-market period is the fraction of variance coming from measurable (DJ) public news similar to the "other public" fraction. This happens both because after-market news is particularly important and because informed traders choose to collect most tractable information that is available during the (prior) regular market period.

6. Testing Predictions from Competing Models

A. Discretionary Liquidity Trader Model Predictions

We now use the main model presented in Table 4A for predictive analyses. Given a set of parameter estimates, the model makes testable predictions about return variance and trading volume in the a = 1, 2, 3 periods after news occurs in period t:

$$Var(r_{1t+a}) = \sigma^2_{\varepsilon t+a} + h_{1t+a}(h_{1t+a} + c)^{-1}\sigma^2_{dt+a+1} + (h_{1t+a-1}/c+1)^{-1}\sigma^2_{dt+a} \tag{26}$$

$$E(v_{1t+a}) = \frac{h_{1t+a}(h_{1t+a}/c+1)}{\sqrt{2\pi}\sigma_{dt+a+1}}\left[1+(h_{1t+a}+c)\sigma^{-1}_{dt+a+1}\sigma^{-1}_{y} + \sqrt{1+c/h_{1t+a}}\right]. \tag{27}$$

The first term in Equation (26) reflects a simplifying assumption that the variance of intractable information is independent of whether first news occurred in the preceding period.[11] Figures 5A, 5B, 5C, and 5D report the predicted hourly return volatility and trading volume from Equations (26) and (27) in event time after news occurs. The lines in the figures represent return volatility and the bars represent volume. The period in which news occurs (t) varies across the figures and the number of periods after news (a) varies along the x-axis within each figure. Each figure shows the actual return volatility and trading volume observed in the data for comparison purposes. Predicted and actual values are all reported in excess of unconditional expectations.

[Insert Figure 5 here.]

Although the model's predictions are simplistic, they can explain two key stylized facts: 1) prices respond to news primarily in the period when news arrives; and 2) volume responds mainly during the regular period, regardless of when news arrives. The most stark and surprising demonstrations of these facts appear in Figures 5B and 5D, which show market activity after news arrives in the pre-market and after-market periods. In both figures, return volatility is by far the highest in the period when news arrives (event period 0), whereas turnover peaks during the regular market period (event period 1 for pre-market news; and period 3 for after-market news).

Although it makes some quantitative errors, the model correctly predicts these qualitative patterns in the figures. Variance is highest when news arrives because news releases intractable information, which is immediately incorporated in prices, and most periods following news do not release additional intractable information. Volume is highest during the regular market

[11] The variance of intractable information following a non-news period comes solely from first news, so it is the probability of first news arriving multiplied by the variance of intractable information in first news periods—*i.e.*, the first term in Equation (26).

period even though news immediately lowers entry costs for discretionary liquidity trades. Still, because their entry costs remain lowest during the regular market period, more discretionary liquidity traders choose to enter at this time. Quantitatively, the model does not predict sufficiently large trading volume in the regular market following after-market news arrival in Figure 5D. One could reconcile this with the model by allowing after-market news to exert an especially large impact on *h*, which is reasonable because after-market news releases the most intractable information—*i.e.*, the after-market $\sigma_{\varepsilon 1}$ values are the highest in Table 4. The other notable model error is that actual regular market volatility is higher than predicted following pre-market news arrival (in Figure 5B). This error could arise from the simplifying assumption that the variance of intractable information is unaffected by the presence of recent news, which is violated if regular market news is especially informative following pre-market news.

The empirical patterns observed for regular market and overnight news in Figures 5A and 5C are quite similar to those in 5B and 5D, though two differences arise. First, after regular market news in Figure 5A, return volatility is unusually high in the following pre-market period (event period 3). Surprisingly, the model correctly predicts this delayed increase in variance because expected rebalancing needs net of entry costs are especially high in the pre-market period after news occurs, which induces more informed traders to acquire and trade on private information. A simple economic story is that liquidity traders may read the news in the morning, which would lower their cost of trading in the pre-market period. Second, after overnight news in Figure 5C, pre-market variance is actually slightly higher than overnight variance. The same idea—that discretionary liquidity traders may read the news in the morning—could explain this fact, too, which is why the model is again able to qualitatively match the empirical data.

Lastly, we briefly consider the model's predictions for market liquidity, though we do not quantitatively test them because liquidity in the model's one-shot call auction structure is unlikely to be directly comparable to liquidity observed in continuous double auctions. Previous empirical research shows that market liquidity is higher in the regular market period (Barclay and Hendershott, 2004); b) after news occurs (Tetlock, 2010); and c) in large stocks (Hasbrouck, 2009). The model predicts each of these three features in liquidity data mainly because of variation in the model parameters h and c, neither of which is estimated using liquidity data. Higher rebalancing needs (h) clearly increase liquidity by reducing adverse selection. Lower information acquisition costs (c) also promote liquidity by enticing more informed traders to enter the market, which increases competition and leads to aggressive trading, thereby revealing more private information and improving liquidity.

B. Differences in Opinion Model Predictions

Here we contrast predictions from our model of liquidity trading with those from belief-based models of trading, such as Kim and Verrecchia (1991), Harris and Raviv (1993), Kandel and Pearson (1995), Hong and Stein (2003), and Scheinkman and Xiong (2003). As discussed in Section 2, these theories predict that changes in traders' relative beliefs cause trading, as those with relatively optimistic interpretations of news buy from those with pessimistic interpretations. To test this idea, we analyze market activity around news events sorted on the basis of changes in analysts' beliefs about quarterly earnings.

To measure changes in relative beliefs about news, we consider only news events in which at least two analysts updated an earnings forecast in the four weeks prior to the news and at least one of this same set of analysts updates within one week after the news as recorded in the I/B/E/S database. We compute relative belief changes using the difference between analyst forecast dispersion before and after the news scaled by the firm's stock price four weeks before the news. We use earnings forecasts and stock prices that are adjusted to account for splits. We group news events by terciles ranked by whether analyst beliefs converge (the bottom tercile of relative belief changes), remain similar (middle tercile), or diverge (top tercile).

For news in each tercile of belief changes, we measure hourly return volatility and turnover in the period when news arrives and the following three periods. Figures 6A, 6B, 6C, and 6D report these measures for news events arriving in each of the four intraday periods. The three bars in each figure depict turnover occurring after each type of news event—convergence, no change, or divergence in analysts' relative beliefs—while the three lines represent volatility after each type of news.

[Insert Figure 6 here.]

The patterns in the four figures do not support belief-based models of trading activity. For example, in Figure 6B showing responses to pre-market news, turnover is very similar in each event period regardless of whether analysts' relative beliefs changed significantly around news. The same observation applies to Figures 6A, 6C, and 6D. This finding casts doubt on the idea that investor disagreement is a major determinant of trading activity after news. An alternative interpretation is that analysts' beliefs are such a poor proxy for investors' beliefs that their relationship with trading activity cannot be observed. However, this latter interpretation would call into question a voluminous empirical literature that uses analyst forecast dispersion as a proxy for investor disagreement—*e.g.*, Diether, Malloy, and Scherbina (2002) and Chordia, Huh, and Subrahmanyam (2007) among many others.[12]

Like the previous figures, Figures 6A through 6D show that return volatility after news typically occurs immediately in event period 0, whereas most trading volume that follows news events occurs in the regular market. This delayed volume response is difficult to reconcile with

[12] A recent paper by Giannini and Irvine (2012) advocates using a novel difference of opinion measure based on disagreement between the tone of media coverage and posts on stocktwits.com.

differences in opinion models. The timing of volatility implies that market prices aggregate most traders' beliefs in event period 0, which suggests that most belief-based trading occurred in event period 0, too. But most trading following news occurs in the regular market, which is not typically event period 0, implying that most trading is not driven by beliefs. In contrast, the timing of volatility and volume can be reconciled with models of discretionary liquidity traders. If these traders expect their trades to have less impact on prices when news has less impact on beliefs, they would choose to enter the market and trade after such news events.

7. Concluding Discussion

We estimate a structural model of strategic trader behavior to match the rich relationships between volume, volatility, and news arrival in the electronic trading era. For the model to fully explain the magnitude of the volume and volatility patterns across the intraday periods, discretionary liquidity trading must constitute the vast majority of overall trading volume—*e.g.*, 92% in the regular market. Although the model is a simplification of reality, it suggests that policymakers should carefully consider the welfare of such uninformed traders when evaluating alternative market structures and regulations. In the model, because there is perfect competition among market makers and among informed traders, welfare is solely determined by the surplus received by liquidity traders. The inframarginal traders with the highest rebalancing needs net of entry costs receive aggregate surplus given by:

$$\sum_{j=1}^{k_t} h_t / j - k_t (h_t / k_t) = h_t (\sum_{j=1}^{k_t} 1/ j - 1) \approx h_t \ln(2k_t / 3) \text{ for } k_t >> 1. \quad (28)$$

This surplus increases with the number of liquidity traders who enter the market, suggesting broad participation in trading is a reasonable proxy for welfare. Because the number of liquidity traders is proportional to market liquidity in equilibrium, improvements in liquidity also signify improvements in welfare. Thus, our model provides a theoretical basis for the participation and liquidity objectives that the SEC often cites among its central goals.

Furthermore, our parameter estimates imply the cost of acquiring and acting on information fell sharply in the past decade, causing increases in participation and liquidity and thus trader welfare. This positive account of the impact of advances in trading technology on trader welfare contrasts with more negative populist arguments. Such arguments typically ignore the possibilities that uninformed agents can choose whether to trade and that informed traders aggressively compete against each other. Because it includes these two key features, our model predicts that technological advances can improve liquidity and price discovery, both of which can be socially beneficial.

We show that this model correctly predicts that stock prices respond immediately to news, while trading volume typically responds with a delay. News not only releases intractable information, which is priced immediately, but it also triggers trader attention for an extended period of time. During this window, uninformed traders choose to enter the market when it is cheapest to trade—usually in regular trading hours—regardless of when news arrives.

This emphasis of the role of discretionary liquidity traders and trading frictions contrasts with recent models that highlight the importance of changes in traders' relative beliefs. Although many patterns in volume, volatility, and news can be explained without resorting to trader disagreement, a model that includes both trading frictions *and* disagreement is likely to produce an even richer set of predictions. The welfare implications of a model in which traders' sometimes act on irrational beliefs are also likely to differ from those discussed above. Future researchers could estimate and test such a model using data on individual traders, which could allow for separate estimates of disagreement, attention constraints, and rebalancing needs.

Appendix

Solving the Model

Here we solve for the equilibrium strategies and endogenous outcomes in the model introduced in Section 2. For an informed trader *i* who acquires a signal d_{t+1} and chooses to trade an amount x_{it}, her expected profits (π_{it}) are given by:

$$E[\pi_{it} \mid d_{t+1}] = E[x_{it}(F_{t+1} - p_t) \mid d_{t+1}] = x_{it}[1-(m_t-1)\lambda_t\beta_t]d_{t+1} - \lambda_t x_{it}^2. \tag{29}$$

Maximizing this quadratic equation in x_{it} gives:

$$x_{it} = \frac{1}{2}[1/\lambda_t - (m_t-1)\beta_t]d_{t+1}. \tag{30}$$

To identify a symmetric equilibrium, we equate the β_t coefficient in the optimal x_{it} strategy with the conjectured linear strategy above:

$$\beta_t = (1/\lambda_t)(m_t+1)^{-1}. \tag{31}$$

The equilibrium market depth can be found from the zero profit condition for the market maker:

$$\lambda_t = \frac{Cov(Q_t, d_{t+1})}{Var(Q_t)} = \frac{\sigma_{dt+1}}{(m_t+1)\sigma_{yt}}\sqrt{\frac{m_t}{k_t}}. \tag{32}$$

The second-order condition for informed traders' maximization problem is $\lambda > 0$, which is always satisfied when there are some liquidity traders—*i.e.*, $k_t\sigma_{yt} > 0$.

Based on their benefits from rebalancing and information acquisition costs, the discretionary liquidity traders and informed traders simultaneously choose whether to enter the market, which endogenously determines m_t and k_t in equilibrium. After substitutions and simplification, the expected trading profit of each informed trader is:

$$E[\pi_{it} \mid d_{t+1}] = \frac{\sigma_{d+1}\sigma_{yt}}{(m+1)}\sqrt{\frac{k_t}{m_t}}. \tag{33}$$

Entry of informed traders occurs until the marginal trader attains zero profits, which occurs when $E[\pi_{it}|d_{t+1}] = c$ or:

$$c^2 m_t(m_t+1)^2 = k_t\sigma_{yt}^2\sigma_{dt+1}^2. \tag{34}$$

This implies that equilibrium illiquidity is:

$$\lambda_t = \frac{\sigma_{dt+1}^2}{c(m+1)^2}. \tag{35}$$

The (negative) expected trading profit (π_{jt}) of each discretionary liquidity traders is:

$$E[\pi_{jt}] = E[y_{jt}(F_{t+1} - p_t)] = -\lambda_t E[y_{jt}^2] = -\frac{\sigma_{dt+1}^2 \sigma_{yt}^2}{c(m_t+1)^2}, \tag{36}$$

where the second equality uses the equilibrium entry condition for informed traders.

Entry of discretionary liquidity traders occurs until the marginal trader's expected trading loss is equal to his expected benefit from rebalancing (h_t/k_t), when the equilibrium number of liquidity traders will be

$$k_t = ch_t(m_t+1)^2 \sigma_{dt+1}^{-2} \sigma_{yt}^{-2}. \tag{37}$$

Substituting this condition into the informed trader's zero profit condition, we obtain the equilibrium number of informed traders:

$$m_t = h_t / c. \tag{38}$$

Substituting this value of m_t into the k_t equation gives the equilibrium solution for k_t reported in the text, which then allows one to compute the reported equilibrium values of λ_t and β_t.

Measuring Returns Using TAQ Data

During regular trading, we only keep trades and quotes meeting standard filters used in the microstructure literature. We drop trades with non-positive price or size and those with correction codes not equal to zero or condition code of M, Q, T, or U. For the pre-market and after-market periods, however, the filters for trades necessarily differ. Most importantly, we do not exclude trades with a condition code of T, which explicitly identifies extended hours trades. For extended hours periods, we exclude those that occur at prices probably determined within the trading day (*e.g.*, crosses and block trades), appear out of sequence, or contain non-standard delivery options. This filter eliminates any trades from NYSE, AMEX, or CBOE and trades with "cond" codes B, G, K, M, L, N, O, P, W, U, Z, 4, 5, 6, 8, or 9. We drop trades of at least 10,000 shares or $200,000 regardless of their "cond" codes as these are likely pre-negotiated blocks. Finally, we drop all trades and quotes in the final minute of the pre-market and in the first minute of the after-market period to mitigate effects of bid-ask bounce.

Within each of the pre-market, regular, and after-market periods, we construct a beginning and ending trade price as the volume-weighted average price (VWAP) based on the first and last minute of trades in the dataset and then compute trade-based returns. Using a VWAP instead of a single trade price further mitigates the effects of bid-ask bounce in returns. The overnight period return is the percent change from the last after-market price to the first pre-market price on the subsequent trading day, accounting for dividends and stock splits when the subsequent trading day is the ex date. When there is only one trade observation in an intraday period, its return is computed from the last price from the most recent intraday period. When there is no trading in a period, the return is zero. CRSP computes a stock return on trading day t based on the last regular hours transaction (or quote, in the event of non-trading) prices on day t and $t - 1$. Ignoring our 1-minute buffers at the end of the pre-market and the beginning of the after-market periods, day t CRSP return is approximated by compounding our after-market return from day $t - 1$ and our overnight, pre-market, and regular period returns on day t.

Bibliography

Admati, Anat R., and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Bamber, Linda Smith, Orie E. Barron, and Douglas E. Stevens, 2011, Trading volume around earnings announcements and other financial reports: Theory, research design, empirical evidence, and directions for future research, *Contemporary Accounting Research* 28, 431-471.

Banerjee, Snehal, and Ilan Kremer, 2010, Disagreement and learning: Dynamic patterns of trade, *Journal of Finance* 65, 1269-1302.

Barclay, Michael J., and Terrence Hendershott, 2003, Price discovery and trading after hours, *Review of Financial Studies* 16, 1041-1073.

Barclay, Michael J., and Terrence Hendershott, 2004, Liquidity externalities and adverse selection: Evidence from trading after hours, *Journal of Finance* 59, 681-710.

Barclay, Michael J., and Terrence Hendershott, 2008, A comparison of trading and non-trading mechanisms for price discovery, *Journal of Empirical Finance* 15, 839-849.

Barclay, Michael J., Robert H. Litzenberger, and Jerold B. Warner, 1990, Private information, trading volume, and stock-return variances, *Review of Financial Studies* 3, 233-253.

Beaver, William H., 1968, The information content of annual earnings announcements, *Journal of Accounting Research* 6, 67-92.

Berry, Thomas D., and Keith M. Howe, 1994, Public information arrival, *Journal of Finance* 49, 1331-1346.

Brandt, Michael W., Alon Brav, John R. Graham, and Alok Kumar, 2010. The idiosyncratic volatility puzzle: Time trend or speculative episodes? *Review of Financial Studies* 23, 863-899.

Chae, Joon, 2005, Trading volume, information asymmetry, and timing information, *Journal of Finance* 60, 413-442.

Chordia, Tarun, Sahn-Wook Huh, and Avanidhar Subrahmanyam, 2007, The cross-section of expected trading activity, *Review of Financial Studies* 20: 709-740.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2011, Recent trends in trading activity and market quality, *Journal of Financial Economics* 101, 243-263.

Cutler, David M., James M. Poterba, and Lawrence H. Summers, 1989, What moves stock prices? *Journal of Portfolio Management* 15, 4-12.

DeBondt, Werner F.M., and Richard H. Thaler, 1995, Financial decision-making in markets and firms: A behavioral perspective, In *Handbooks in Operations Research and Management Science: Finance*. Edited by Robert A. Jarrow, Vojislav Maksimovic, and William T. Ziemba. Amsterdam: Elsevier: 385-410.

Diether, Karl B, Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113-2141.

Fang, Lily, and Joel Peress, 2009, Media coverage and the cross-section of stock returns, *Journal of Finance* 64, 2023-2052.

French, Kenneth R., 2008, The cost of active investing, *Journal of Finance* 58, 1537-1573.

French, Kenneth R., and Richard Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics* 17, 5-26.

Giannini, Robert, and Paul J. Irvine, 2012, The impact of divergence of opinions about earnings within a social network, working paper, University of Georgia.

Harris, Milton, and Artur Raviv, 1993, Differences of opinion make a horse race, *Review of Financial Studies* 6, 473-506.

Hong, Harrison, and Jeremy C. Stein, 2003, Differences of opinion, short-sales constraints, and market crashes, *Review of Financial Studies* 16, 487-525.

Ito, Takatoshi, Richard K. Lyons, and Michael T. Melvin, 1998, Is there private information in the FX market? The Tokyo experiment, *Journal of Finance* 53, 1111-1130.

Jain, Prem C., and Gun-Ho Joh, 1988, The dependence between hourly prices and trading volume, *Journal of Financial and Quantitative Analysis* 23, 269-283.

Jiang, Christine X., Tanakorn Likitapiwat, and Thomas McInish, 2011, Information content of earnings announcements: Evidence from after hours trading, *Journal of Financial and Quantitative Analysis*, forthcoming.

Jones, Charles M., Gautam Kaul, and Marc L. Lipson, 1994, Information, trading, and volatility, *Journal of Financial Economics* 36, 127-154.

Kandel, Eugene, and Neil D. Pearson, 1995, Differential interpretation of public signals and trade in speculative markets, *Journal of Political Economy* 103, 831-872.

Kim, Oliver, and Robert E. Verrecchia, 1991, Trading volume and price reactions to public announcements, *Journal of Accounting Research* 29, 302-321.

Kim, Oliver, and Robert E. Verrecchia, 1994, Market liquidity and volume around earnings announcements, *Journal of Accounting and Economics* 17, 41-67.

Kim, Oliver, and Robert E. Verrecchia, 1997, Pre-announcement and event-period private information, *Journal of Accounting and Economics* 24, 395-419.

Kross, William, Gook-Lak Ha, and Frank Heflin, 1994, A test of risk clientele effects via an examination of trading volume response to earnings announcements, *Journal of Accounting and Economics* 18, 67-87.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Mendelson, Haim, and Tunay I., Tunca, 2004, Strategic trading, liquidity, and information acquisition, *Review of Financial Studies* 17, 295-337.

Michaely, Roni, Amir Rubin, and Alexander Vedrashko, 2011, Corporate governance and the timing of earnings announcements, Cornell University working paper.

Milgrom, Paul, and Nancy Stokey, 1982, Information, trade, and common knowledge, *Journal of Economic Theory* 26, 17-27.

Mitchell, Mark L., and J. Harold Mulherin, 1994, The impact of public information on the stock market, *Journal of Finance* 49, 923-950.

Roll, Richard, 1988, R^2, *Journal of Finance* 43, 541-566.

Scheinkman, José A., and Wei Xiong, 2003, Overconfidence and speculative bubbles, *Journal of Political Economy* 111, 1183-1219.

Tetlock, Paul C., 2010, Does public financial news resolve asymmetric information? *Review of Financial Studies* 23, 3520-3557.

Zdorovtsov, Vladimir, 2004, Firm-specific news, extended-hours trading and variances over trading and nontrading periods, State Street Global Advisors working paper.

Table 1: Probability of News Arrival

This table presents probabilities of news arrival during 2001-2010 for each of four intraday periods: the Regular Market (9:30 AM to 4:00 PM), the Pre-Market (7:00 AM to 9:30 AM), Overnight (6:30 PM to the following 7:00 AM), and the After-Market (4:00 PM to 6:30 PM). The variable *news* is 1 if there is at least one story (two stories) in the Dow Jones Newswires mentioning a particular Small or Mid Cap (Large Cap) firm and 0 otherwise. The variable *FirstNews* is 1 if *news*=1 for the current period and *news*=0 for each of the past three intraday periods, and 0 otherwise. All probabilities are calculated by pooling observations for all firms within each year and size group and then averaging across groups. Panels A-D provide results for All, Large Cap, Mid Cap, and Small Cap firms with market capitalizations in the intervals [\$100M, ∞), [\$10B, ∞), [\$1B,\$10B), and [\$100M,\$1B), respectively.

Panel A: All Firms	Regular	Pre-Market	Overnight	After-Market
P(*news*=1)	0.1476	0.1013	0.1189	0.0750
P(*FirstNews*=1)	0.1015	0.0743	0.0850	0.0532
Firms Per Year/Size Group	192			

Panel B: Large Caps				
P(*news*=1)	0.2565	0.1295	0.1612	0.1008
P(*FirstNews*=1)	0.1632	0.0733	0.0855	0.0529
Firms Per Year	95			

Panel C: Mid Caps				
P(*news*=1)	0.1225	0.1036	0.1206	0.0747
P(*FirstNews*=1)	0.0927	0.0860	0.1021	0.0619
Firms Per Year	245			

Panel D: Small Caps				
P(*news*=1)	0.0639	0.0707	0.0750	0.0496
P(*FirstNews*=1)	0.0485	0.0635	0.0675	0.0449
Firms Per Year	237			

Table 2: Hourly Return Volatility

This table presents hourly stock return volatilities during 2001-2010 for each of four intraday periods: the Regular Market, the Pre-Market, Overnight, and the After-Market. Variances are calculated by pooling observations for all firms within each year and size group and then averaging across groups. Conditional measures are based only on observations meeting the condition *FirstNews*=1 or *RecentNews*=0. Panels A-D provide results for All, Large Cap, Mid Cap, and Small Cap firms, respectively. Intraday periods, variables, and subsamples are as defined above. Numbers in the table are converted to hourly volatilities by dividing the variance by the number of hours in the intraday period and then taking the square root. Bootstrapped standard errors appear in parentheses.

Panel A: All Firms	Regular	Pre-Market	Overnight	After-Market
Unconditional	1.275	0.698	0.344	0.811
	(0.019)	(0.013)	(0.007)	(0.016)
FirstNews=1	1.569	1.405	0.611	2.380
	(0.023)	(0.029)	(0.022)	(0.059)
RecentNews=0	1.192	0.479	0.305	0.653
	(0.018)	(0.011)	(0.006)	(0.018)
Panel B: Large Caps				
Unconditional	0.954	0.625	0.271	0.599
	(0.025)	(0.025)	(0.012)	(0.028)
FirstNews=1	0.987	1.003	0.408	2.050
	(0.035)	(0.060)	(0.039)	(0.142)
RecentNews=0	0.901	0.459	0.236	0.445
	(0.025)	(0.018)	(0.013)	(0.030)
Panel C: Mid Caps				
Unconditional	1.177	0.663	0.318	0.760
	(0.018)	(0.014)	(0.006)	(0.018)
FirstNews=1	1.419	1.307	0.511	2.160
	(0.029)	(0.047)	(0.020)	(0.060)
RecentNews=0	1.082	0.450	0.281	0.593
	(0.018)	(0.015)	(0.006)	(0.020)
Panel D: Small Caps				
Unconditional	1.606	0.794	0.425	1.018
	(0.019)	(0.013)	(0.007)	(0.019)
FirstNews=1	2.097	1.790	0.831	2.851
	(0.033)	(0.052)	(0.033)	(0.067)
RecentNews=0	1.511	0.526	0.380	0.854
	(0.019)	(0.012)	(0.007)	(0.020)

Table 3: Hourly Turnover

This table presents hourly turnover during 2001-2010 for each of four intraday periods: the Regular Market, the Pre-Market, Overnight, and the After-Market. Average turnover is calculated by pooling observations for all firms within each year and size group and then averaging across groups. Conditional measures are based only on observations meeting the condition *FirstNews*=1 or *RecentNews*=0. Panels A-D provide results for All, Large Cap, Mid Cap, and Small Cap firms, respectively. Intraday periods, variables, and subsamples are as defined above. Numbers in the table are converted to hourly turnover by dividing the average turnover by the number of hours in the intraday period. Bootstrapped standard errors appear in parentheses.

Panel A: All Firms	Regular	Pre-Market	After-Market
Unconditional	25.62	0.34	0.46
	(0.257)	(0.009)	(0.009)
FirstNews=1	32.50	0.94	2.27
	(0.430)	(0.044)	(0.085)
RecentNews=0	22.39	0.13	0.33
	(0.218)	(0.003)	(0.006)

Panel B: Large Caps			
Unconditional	17.60	0.17	0.24
	(0.181)	(0.004)	(0.008)
FirstNews=1	18.16	0.34	1.45
	(0.329)	(0.019)	(0.093)
RecentNews=0	16.72	0.09	0.17
	(0.167)	(0.002)	(0.003)

Panel C: Mid Caps			
Unconditional	29.38	0.29	0.48
	(0.258)	(0.008)	(0.009)
FirstNews=1	35.10	0.74	2.25
	(0.384)	(0.037)	(0.106)
RecentNews=0	25.38	0.11	0.35
	(0.217)	(0.002)	(0.006)

Panel D: Small Caps			
Unconditional	29.88	0.55	0.66
	(0.437)	(0.024)	(0.017)
FirstNews=1	44.25	1.72	3.12
	(0.968)	(0.125)	(0.170)
RecentNews=0	25.06	0.18	0.47
	(0.361)	(0.006)	(0.011)

Table 4: Estimates of Model Parameters When *h* Varies with News

This table presents efficient GMM estimates of exogenous parameters of the model described in Section 2. Where appropriate, the table reports separate estimates of parameters for each of four intraday periods—the Regular Market, the Pre-Market, Overnight, and the After-Market—and conditional on *news*=1 or 0. Panels A-C provide results based on the Full Sample (2001-2010), 2001-2005, and 2006-2010, respectively. Panels D-F provide results based on Large Cap, Mid Cap, and Small Cap firms, respectively. Intraday periods and subsamples are as defined above. GMM standard errors appear in parentheses.

Panel A: Full Sample	Regular	Pre-Market	Overnight	After-Market
h(news) x 10^{-6}	8.262	1.094		0.741
	(0.248)	(0.055)		(0.045)
h(no news) x 10^{-6}	7.116	0.206		0.140
	(0.229)	(0.005)		(0.017)
c x 10^{-6}	2.132			
	(0.288)			
σ_d	2.552		1.113	2.071
	(0.130)		(0.027)	(0.157)
$\sigma_\varepsilon(news)$	2.580	1.650	1.870	3.586
	(0.061)	(0.064)	(0.084)	(0.095)

Panel B: 2001-2005				
h(news) x 10^{-6}	6.376	1.320		0.654
	(0.362)	(0.084)		(0.041)
h(no news) x 10^{-6}	5.168	0.277		0.101
	(0.308)	(0.010)		(0.008)
c x 10^{-6}	4.037			
	(0.254)			
σ_d	3.338		1.120	1.325
	(0.077)		(0.034)	(0.089)
$\sigma_\varepsilon(news)$	2.975	1.676	2.249	4.359
	(0.088)	(0.095)	(0.133)	(0.147)

Panel C: 2006-2010				
h(news) x 10^{-6}	5.550	0.529		0.802
	(0.153)	(0.023)		(0.033)
h(no news) x 10^{-6}	4.962	0.117		0.285
	(0.136)	(0.004)		(0.009)
c x 10^{-6}	0.333			
	(0.025)			
σ_d	1.292		1.427	2.492
	(0.045)		(0.049)	(0.063)
$\sigma_\varepsilon(news)$	2.135	1.812	1.392	2.560
	(0.081)	(0.071)	(0.070)	(0.082)

Table 4 (continued)

Panel D: Large Caps	Regular	Pre-Market	Overnight	After-Market
h(news) x 10^{-6}	4.273	0.449		0.481
	(0.274)	(0.047)		(0.046)
h(no news) x 10^{-6}	4.136	0.145		0.082
	(0.264)	(0.007)		(0.020)
c x 10^{-6}	0.908			
	(0.312)			
σ_d	1.957		0.869	1.550
	(0.242)		(0.053)	(0.291)
$\sigma_\varepsilon(news)$	1.022	1.117	1.178	3.133
	(0.149)	(0.135)	(0.164)	(0.227)
Panel E: Mid Caps				
h(news) x 10^{-6}	7.558	0.759		0.784
	(0.274)	(0.107)		(0.065)
h(no news) x 10^{-6}	6.683	0.167		0.203
	(0.225)	(0.008)		(0.050)
c x 10^{-6}	1.138			
	(0.456)			
σ_d	1.991		1.078	2.203
	(0.295)		(0.061)	(0.255)
$\sigma_\varepsilon(news)$	2.328	1.638	1.511	3.238
	(0.085)	(0.103)	(0.082)	(0.097)
Panel F: Small Caps				
h(news) x 10^{-6}	12.007	2.062		0.903
	(0.320)	(0.103)		(0.053)
h(no news) x 10^{-6}	9.395	0.298		0.153
	(0.267)	(0.009)		(0.010)
c x 10^{-6}	4.947			
	(0.275)			
σ_d	3.489		1.365	2.263
	(0.068)		(0.026)	(0.094)
$\sigma_\varepsilon(news)$	3.672	2.105	2.612	4.275
	(0.104)	(0.109)	(0.125)	(0.110)

Table 5: Alternate Estimates of Model Parameters

This table presents efficient GMM estimates of exogenous parameters of the model described in Section 2. Where appropriate, the table reports separate estimates of parameters for each of four intraday periods—the Regular Market, the Pre-Market, Overnight, and the After-Market—and conditional on *news*=1 or 0. In Panel A, the σ_d parameter varies with news. In Panel B, the σ_y parameter is 2 basis points in the Regular period and 0.2 basis points in other periods. Intraday periods and subsamples are as defined above. GMM standard errors appear in parentheses.

Panel A: σ_d Varies with News

	Regular	Pre-Market	Overnight	After-Market
$h \times 10^{-6}$	7.125	0.206		0.141
	(0.228)	(0.005)		(0.017)
$c \times 10^{-6}$	2.119			
	(0.292)			
$\sigma_d(news)$	0.759		0.373	1.711
	(0.049)		(0.012)	(0.131)
$\sigma_d(no\ news)$	2.547		1.113	2.078
	(0.133)		(0.027)	(0.159)
$\sigma_\varepsilon(news)$	2.800	2.209	1.870	3.629
	(0.069)	(0.045)	(0.084)	(0.094)

Panel B: σ_y = 2 Basis Points for the Regular Period

	Regular	Pre-Market	Overnight	After-Market
$h(news) \times 10^{-6}$	12.797	0.636		0.924
	(0.372)	(0.027)		(0.024)
$h(no\ news) \times 10^{-6}$	10.994	0.171		0.311
	(0.326)	(0.005)		(0.008)
$c \times 10^{-6}$	0.502			
	(0.040)			
σ_d	1.505		1.372	2.809
	(0.045)		(0.033)	(0.050)
σ_ε	2.592	1.915	1.871	3.550
	(0.060)	(0.050)	(0.084)	(0.096)

Table 6: Trading Volume and Return Variance Decompositions

This table decomposes trading volume and return variance using the model introduced in Section 2. The values below result from substituting the estimates of the model parameters in Table 4 into Equations (21) to (25). Panels A-D provide sets of decompositions for the Regular Market, Pre-Market, Overnight, and After-Market periods, respectively. Each panel contains results for the Full Sample (2001-2010), 2001-2005, and 2006-1020 as well as Large Cap, Mid Cap, and Small Cap firms. Numbers in the sample are fractions of either trading volume or return variance.

	Volume Decomposition			Variance Decomposition		
Panel A: Regular	Liquidity	Market Maker	Informed	News	Other Public	Private
Full Sample	0.921	0.022	0.057	0.068	0.598	0.334
2001-2005	0.947	0.017	0.036	0.060	0.857	0.083
2006-2010	0.846	0.040	0.114	0.072	0.163	0.765
Large Caps	0.892	0.030	0.079	0.031	0.607	0.362
Mid Caps	0.902	0.026	0.072	0.062	0.426	0.513
Small Caps	0.943	0.017	0.040	0.042	0.739	0.219
Panel B: Pre-Market						
Full Sample	0.738	0.123	0.138	0.174		0.826
2001-2005	0.769	0.123	0.107	0.151		0.849
2006-2010	0.614	0.134	0.252	0.298		0.702
Large Caps	0.633	0.168	0.199	0.110		0.890
Mid Caps	0.690	0.135	0.175	0.229		0.771
Small Caps	0.802	0.103	0.095	0.191		0.809

Table 6 (continued)

Panel C: Overnight	Volume Decomposition: Liquidity	Market Maker	Informed	Variance Decomposition: News	Other Public	Private
Full Sample				0.204	0.796	
2001-2005				0.230	0.770	
2006-2010				0.147	0.853	
Large Caps				0.146	0.854	
Mid Caps				0.191	0.809	
Small Caps				0.203	0.797	
Panel D: After-Market						
Full Sample	0.838	0.084	0.077	0.379	0.547	0.074
2001-2005	0.876	0.079	0.046	0.494	0.469	0.037
2006-2010	0.638	0.115	0.247	0.222	0.209	0.569
Large Caps	0.781	0.100	0.119	0.485	0.404	0.111
Mid Caps	0.795	0.088	0.117	0.405	0.439	0.156
Small Caps	0.877	0.077	0.046	0.306	0.658	0.036

Figure 1: News Probabilities Over Time

This figure shows how probabilities of news arrival for each of four intraday periods (the Regular Market, the Pre-Market, Overnight, and the After-Market) vary by year during 2001-2010. The indicator variable *news* is 1 if there is at least one story (two stories) in the Dow Jones Newswires mentioning a particular Small or Mid Cap (Large Cap) firm and 0 otherwise. All probabilities are calculated by pooling observations for all firms within each year and size group and then averaging across size groups. Intraday periods are as defined above.

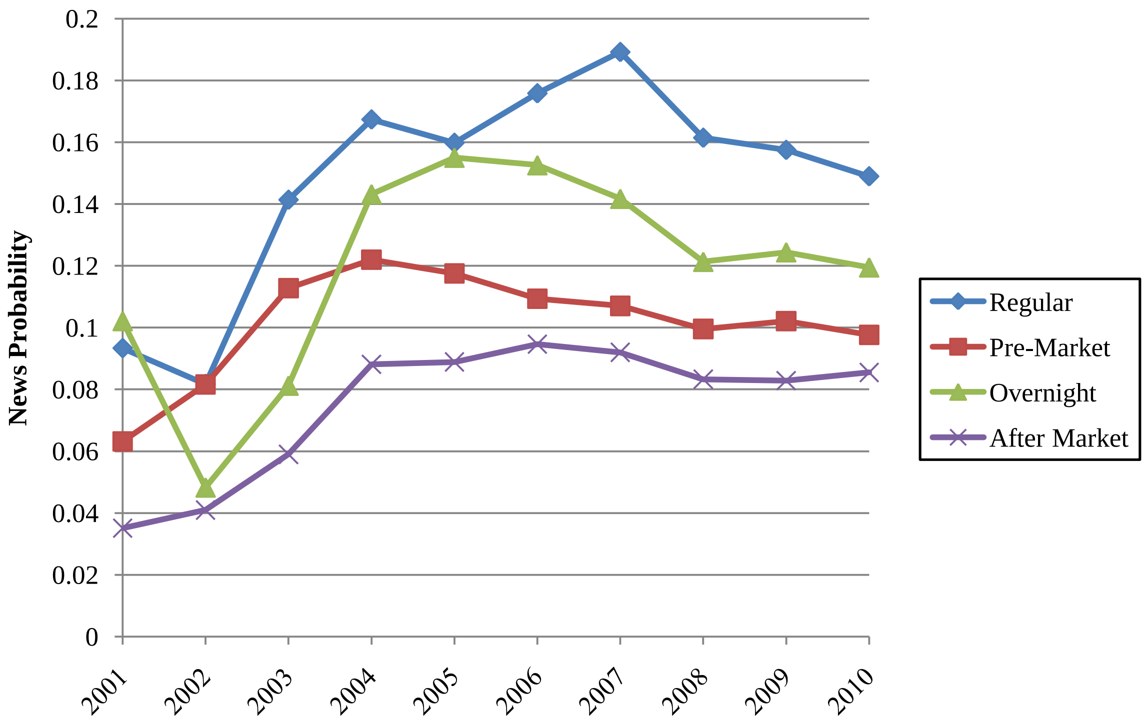
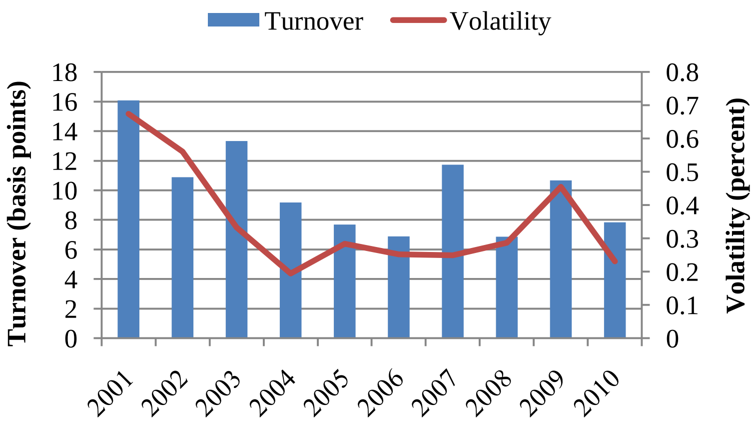
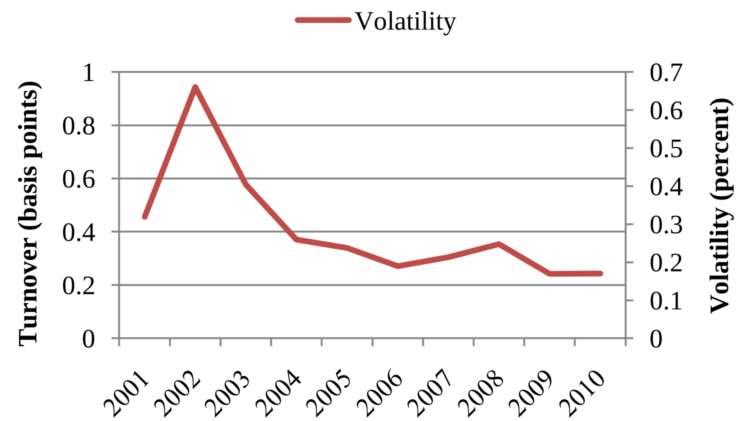


Figure 2: Differences in News and Non-news Hourly Turnover and Volatility.
This figure shows how hourly turnover (bars) and volatility (lines) for news and non-news periods vary by year during 2001-2010. News (non-news) periods are intraday periods with *FirstNews* = 1 (*RecentNews*=0). Panels A-D represent the Regular Market, Pre-Market, Overnight, and After-Market periods, respectively. Intraday periods and variables are as defined above.

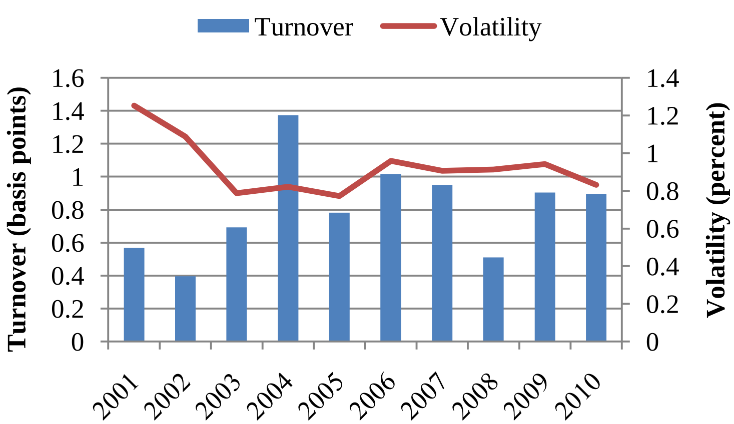
Panel A. Regular Market.



Panel C. Overnight.



Panel B. Pre-Market.



Panel D. After-Market

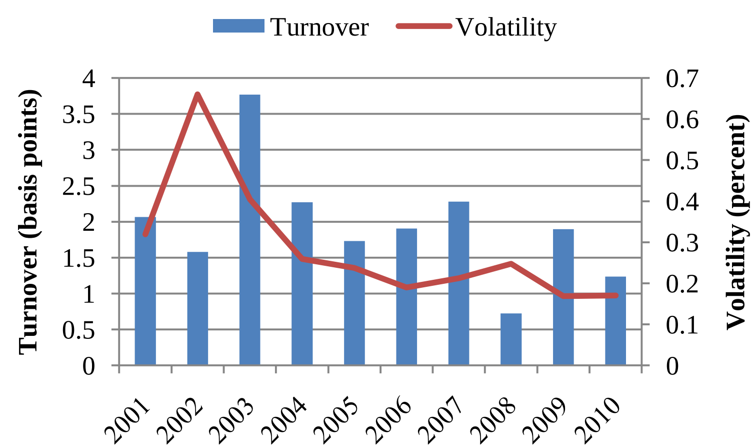
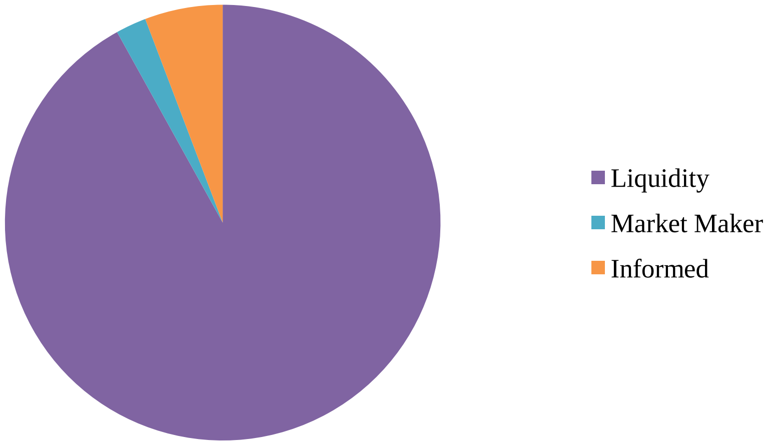
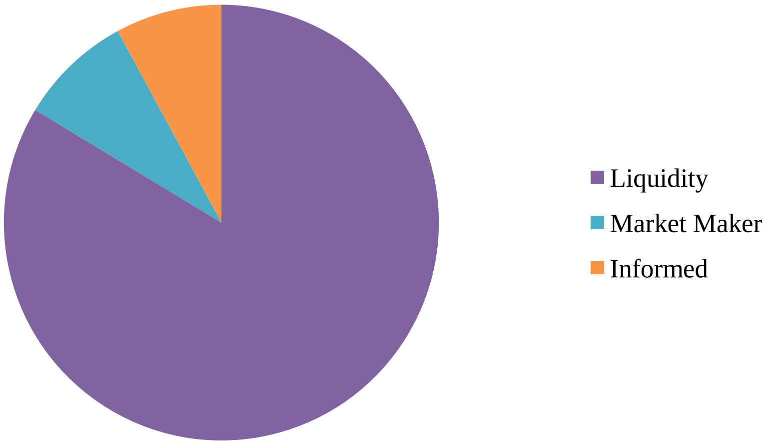


Figure 3: Trading Volume Decompositions
This figure decomposes trading volume during 2001-2010 according to Equations (21) to (24). Panels A-C provide decompositions for the Regular Market, Pre-Market, and After-Market periods, respectively.

Panel A. Regular Market Volume



Panel C. After-Market Volume



Panel B. Pre-Market Volume

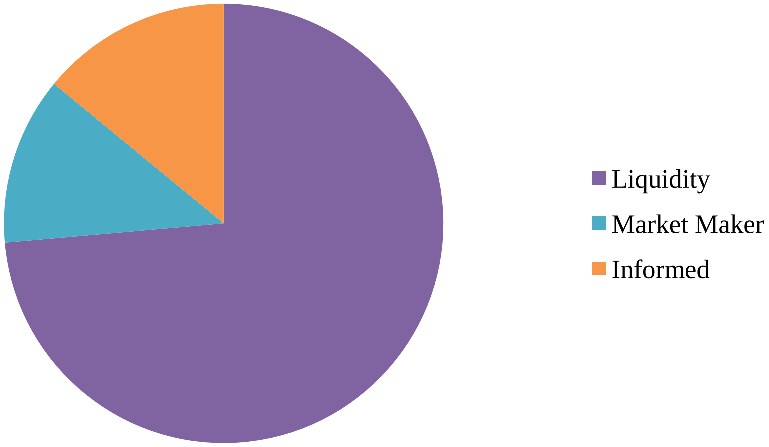
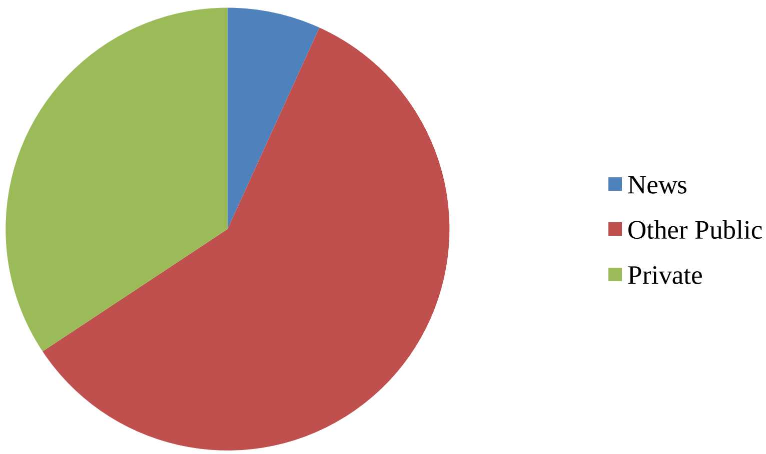
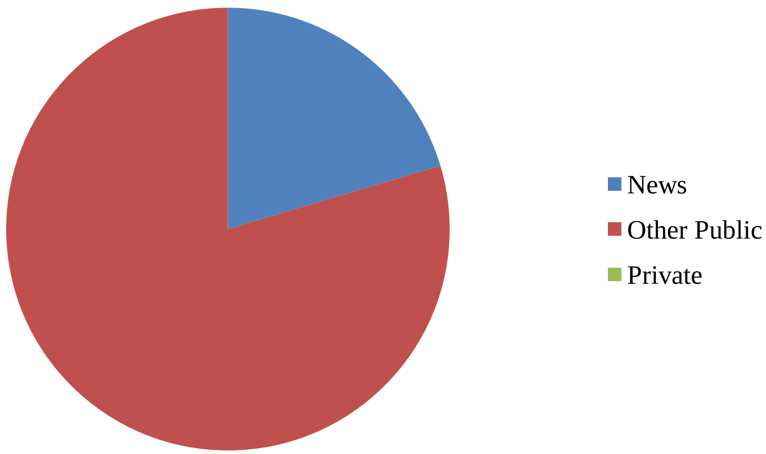


Figure 4: Return Variance Decompositions
This figure decomposes return variance during 2001-2010 according to Equation (25). Panels A-D provide decompositions for the Regular Market, Pre-Market, Overnight, and After-Market periods, respectively.

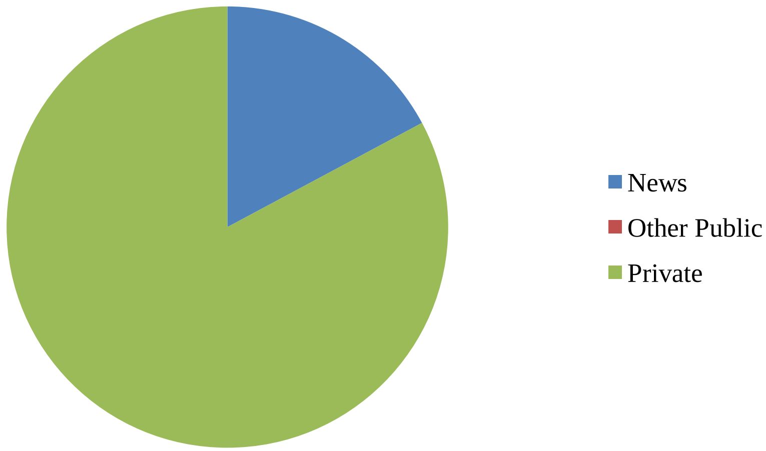
Panel A. Regular Period Variance



Panel C. Overnight Variance



Panel B. Pre-Market Variance



Panel D. After-Market Variance

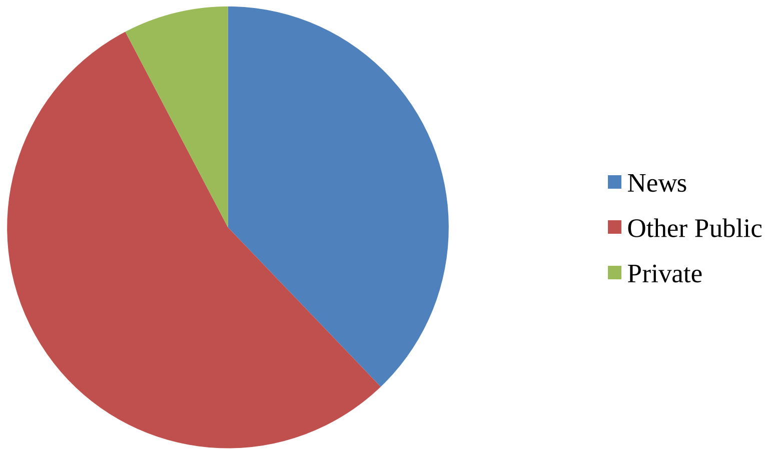
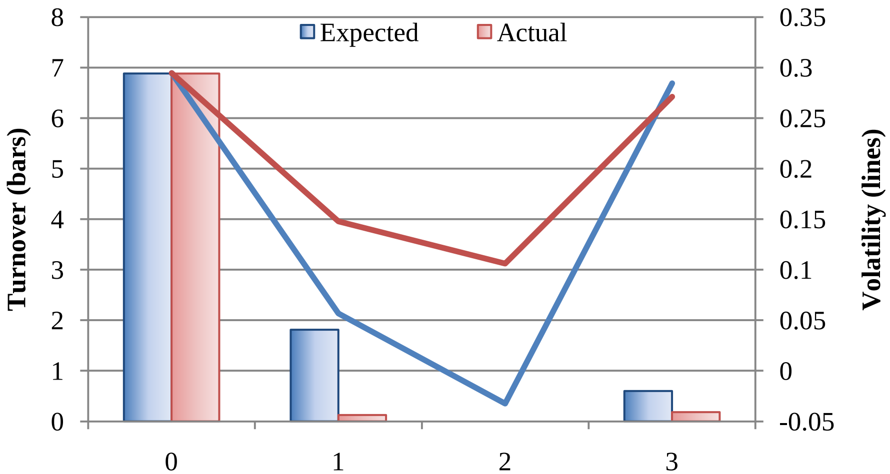


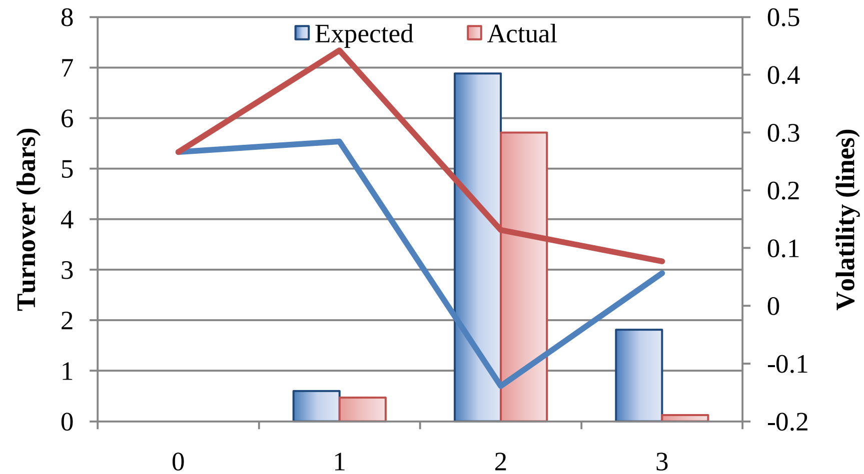
Figure 5: Event-Time Hourly Turnover and Volatility Following News

This figure presents predicted and actual hourly turnover and volatility for intraday periods surrounding news arrival (*FirstNews*=1). The predictions come from Equations (26) and (27) in Section 6, using the model parameters from the Full Sample estimates in Table 4. The horizontal access is the period, in event time, relative to the arrival of news. Panels A-D represent news that arrives in the Regular Market, Pre-Market, Overnight, and After-Market periods, respectively. Predicted and actual values are all reported in excess of unconditional expectations. Intraday periods and variables are as defined above.

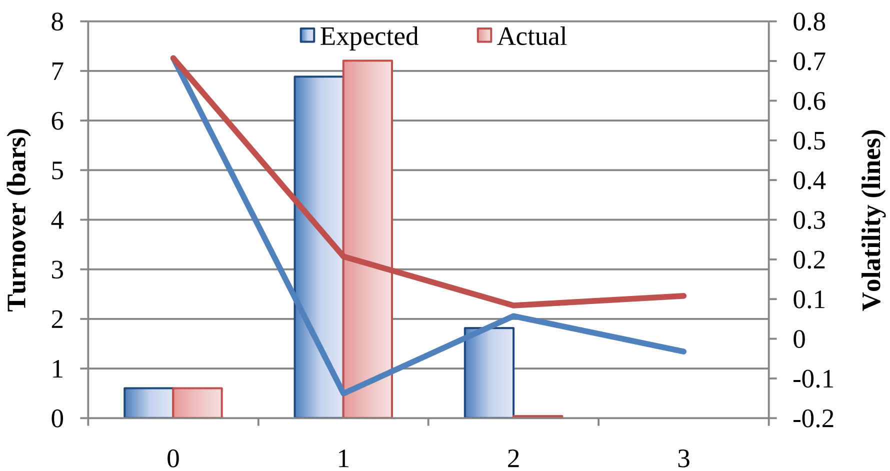
Panel A. Regular Market News



Panel C. Overnight News



Panel B. Pre-Market News



Panel D. After-Market News

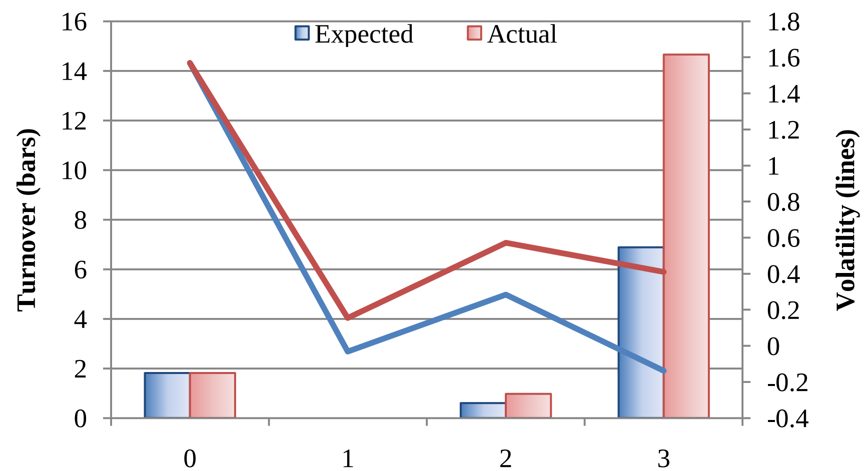
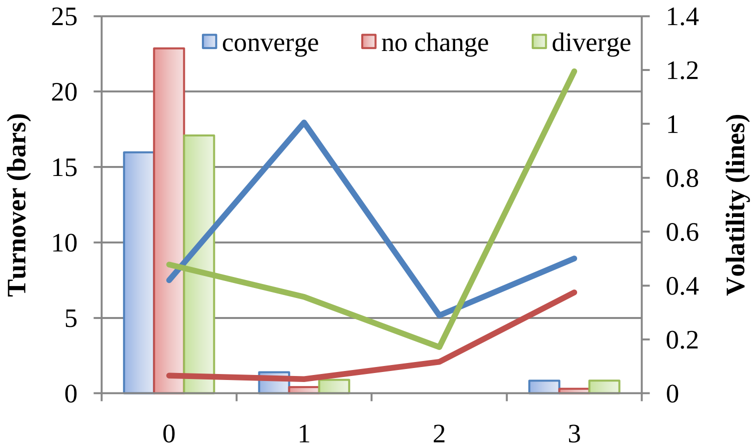
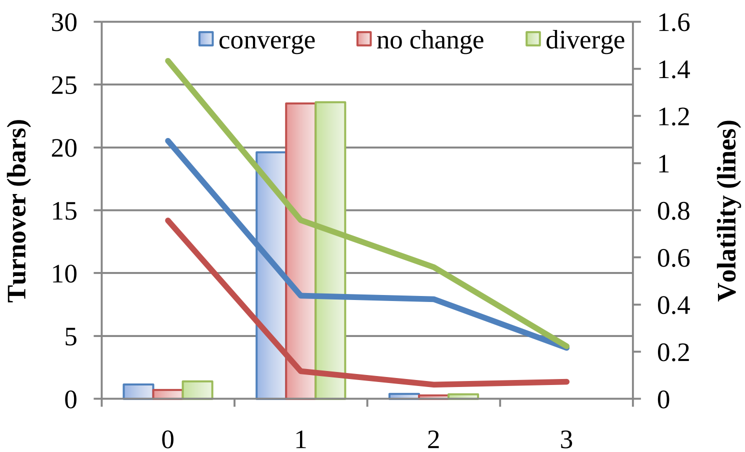


Figure 6: Event-Time Hourly Turnover and Volatility Following News Sorted by Change in Analyst Forecast Dispersion
This figure presents predicted and actual hourly turnover and volatility during 2001-2010 for intraday periods surrounding news arrival (*FirstNews*=1). The predictions come from Equations (26) and (27) in Section 6, using the model parameters from the Full Sample estimates in Table 4. The horizontal access is the period, in event time, relative to the arrival of news. Panels A-D represent news that arrives in the Regular Market, Pre-Market, Overnight, and After-Market periods, respectively. Predicted and actual values are all reported in excess of unconditional expectations. Each panel provides separate analysis using news events associated with convergence, no change, or divergence in analysts' quarterly earnings forecasts. These three groups are based on news events in which at least two analysts provide updates in the four weeks prior to the news and at least one updates in the week following the news. Intraday periods and variables are as defined above.

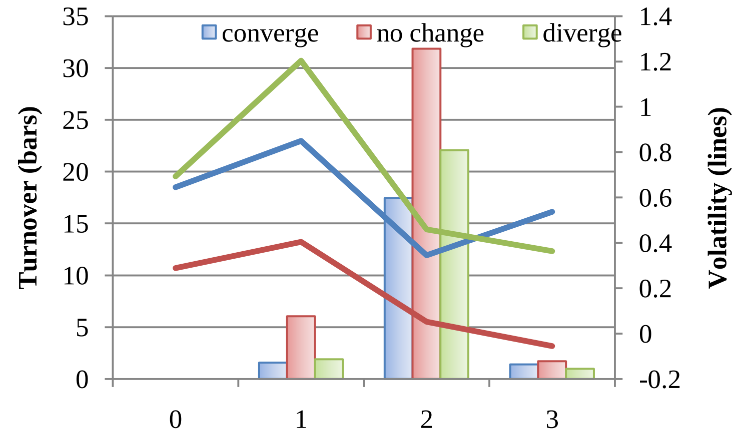
Panel A. Regular Market News



Panel B. Pre-Market News



Panel C. Overnight News



Panel D. After-Market News