Why Does Public News Augment Information Asymmetries?

Julio A. Crego*

Abstract

The arrival of a public signal worsens the adverse selection problem if informed investors are risk averse. Precisely, the public signal reduces uncertainty which boosts informed investors' participation leading to a more toxic order flow. I confirm the model's empirical predictions by estimating the effect of the publication of the weekly change in oil inventories on liquidity via a difference-in-differences strategy. I show the mean bid-ask spread doubles immediately after the release and volume increases by 32 % regardless of the report's surprise. Further, in line with the model, implied volatility drops and insider's trading increases after the report's publication.

Keywords: Public Information, News Release, Asymmetric Information, Liquidity.

JEL: G12, G14.

* *Tilburg University.* I am indebted to my Ph.D. advisor Dante Amengual for his encouragment and useful comments. For helpful suggestions, I also thank Manuel Arellano, Fabio Braggion, Sabrina Buti, Guillermo Caruana, Julio Gálvez, Thomas Gehrig, María Teresa González Pérez, Carolina Manzano, Monica Martinez-Bravo, Roberto Pascual, José Penalva, Rafael Repullo, Enrique Sentana, and Mark van Achter. Financial support from the Santander Research Chair at CEMFI is gratefully acknowledged. Errors and omissions are exclusively my own responsibility. *Email: jacrego@uvt.nl*

A large empirical literature has established that most public announcements, contrary to common intuition, augment information asymmetries.[1] Kim and Verrecchia (1994) explains this fact through asymmetries in the learning technology: even if every investor observes the signal, only a few might be able to interpret it; hence public announcements provide private information. Although this channel might play a major role during earnings announcements, its role in other situations might be minor. For instance, this channel implies that governmental institutions spend public resources to release macroeconomic data which, instead of leveling the playing field, favors a few investors. Yet, previous literature neither provides an alternative channel to the increase in information asymmetries nor empirical evidence in favor of different technologies.

This paper shows that asymmetries due to different learning technologies cannot explain the increase in information asymmetries around some announcements, proposes an alternative mechanism, and provides new empirical evidence to support the novel mechanism. The novel mechanism becomes relevant when every investor learns equally about the asset from the public announcement. Therefore, reconciles the increase in information asymmetries and the benevolent objective of providing the same information to every investor.

Testing the presence of Kim and Verrecchia (1994)'s channel reduces to test the existence of a link between the content of the announcement and the boost in volume at the moment of the release.[2] When the public announcement differs strongly from its expectation, those investors who learn from it have a high informational advantage and trade significantly. On the other hand, these investors barely trade if the announcement is close to its expectation due to the small informational advantage. Empirically, nonetheless, we might not observe the link because of information leakages before the announcement, a noisy measure of the content, other factors that affect volume at the

[1] Prior literature has shown this empirical fact after earning announcements (Lee, Mucklow, and Ready, 1993; Krinsky and Lee, 1996), macroeconomic releases (Green, 2004) and Reuters releases (Riordan, Storkenmaier, Wagener, and Zhang, 2013) among other publications.

[2] Similarly, Bollerslev, Li, and Xue (2018) relies on the link between volume and volatility.

same time of the announcement, or a strategic choice of the release time according to the content and market participants' attention. Therefore, a comprehensive analysis of public announcements will not result in a credible empirical exercise. Instead, I present a counterexample: an announcement that increases information asymmetries and volume but in which previous mechanisms do not play a significant role.

I focus on the publication of the Weekly Petroleum Status (WPS) report because it provides an appropriate setting for a credible empirical exercise. This document, which is released by the Energy Information Administration (EIA) every Wednesday at 10:30 a.m., contains the official oil inventory levels in the US and has four features necessary to test the empirical hypotheses of the model: First, it is crucial for pricing. I show that returns on Wednesdays at 10:30 a.m. are 28 times more volatile than the median minute. Second, unlike earnings announcements or press articles, the information content of the oil inventory report has a clear implication for oil prices. Specifically, an unexpected inventory buildup is a signal of a negative shock in demand or a positive shock in supply which entails a decrease in prices. Third, the information is released automatically at a specific time, 10:30 a.m. This feature ensures that the release time does not depend on the signal realization, and allows me to identify the intraday dynamics of the effect. Fourth, the report release affects firms highly dependent on oil, while the remaining sectors do not react to the report. I use this last feature to design a difference-in-differences strategy. The first difference considers firms whose main input is oil as treated, and the remaining firms make up the control group. Meanwhile, the second difference compares Wednesdays with the remaining weekdays. I conduct the estimation across days and firms using data from a given minute. As a result, I identify the effect of the public release at every minute controlling for market-wide changes.

Empirical results coincide with previous literature: prices react to the announcement, and volume and bid-ask spread increase. If the widening of spreads emerges from differences in learning, volume will rise according to the signal; in this case, the change in inventories minus its expected value. I show that this is not the case. At the moment of the announcement, volume boosts by 32% and bid-ask spreads widen by 2.78 bps, independently of the unexpected change in inventories. These results remain valid if the signal content is substituted by its absolute value, if negative and positive values are allowed to have a different effect or if we divide the signal domain using binary variables, which supports the idea of independence between spreads and volume and the change in inventory. Altogether, there must be another mechanism that explains higher information asymmetries and higher volume independent of the announcement surprise.

The mechanism I propose hinges on how a public signal endogenously changes the composition of traders in the market due to risk aversion. Consider a market in which there are two types of traders. The first one comprises investors with liquidity or hedging needs, thus they sell and buy for exogenous reasons. Meanwhile, the second group consists of risk averse speculators who own some private information about the asset and trade to monetize their informational advantage. To connect these agents, a third agent, the market maker, provides liquidity to both sides of the market, ignoring the type of each trader. Glosten and Milgrom (1985) shows that this last agent provides a spread between the price to buy and the price to sell such that the loses from informed investors compensate the gains from the remaining traders.

Before the arrival of the signal, some informed agents refrain from trading because the gains from their informational advantage do not compensate the risk due to the remaining uncertainty about the asset value. When they have observed the signal, part of the uncertainty is resolved and they enter the market; at the same time, the market maker realizes that the adverse selection problem has worsened and widens the spread. Afterward, since a more informative order flow enhances learning from trades, information rents shrink inducing a reduction in spreads and informed trading. Therefore, the effect on volume and spreads diminishes over time and it finally dissipates.

The model provides clear empirical predictions that coincide with the empirical results. First, prices, volume, and bid-ask spreads should not be affected by the public signal before its release. At that time, the model predicts that prices react to the content of the announcement, and bid-ask spreads and volume increase. Afterward, prices should remain constant forever in expectation while volume and spreads should decrease over time until these variables return to the levels in the case of the absence of public news. Furthermore, according to the model, these movements in spreads and volume are independent of the public signal's realization since they are driven by the reduction in uncertainty.

Although the empirical results line up with the output of the model, they are not a direct test of the mechanism. Then, I provide additional evidence in favor of the two main ingredients of the model: a reduction in uncertainty after the release and an increment in informed trading. On the one hand, using options prices and the same difference-in-differences strategy, I show that implied volatility decreases on Wednesday. On the other hand, SEC filings reveal that, on Wednesdays, insiders of oil firms trade 15% more than their nonoil counterparts, taking their differences into account through the difference-in-differences approach. Additionally, neither the increase in insider volume nor its sign relates to the content of the announcement.

The model also predicts heterogeneity across reports. When the relevance of the report is high, it resolves more uncertainty which leads to a stronger reaction of volume and spreads. I show that a one standard deviation increase in the relevance of the report augments the effect on volume and spreads by a third. To estimate the relevance of the report ex-ante, I exploit the term-structure of options written on oil firms as proposed by Dubinsky, Johannes, Kaeck, and Seeger (2019).

There are alternative mechanisms to Kim and Verrecchia (1994)'s proposed in the literature to explain the market reaction around public announcements. Tetlock (2010) argues that public announcements disclose part of the privately held information and therefore reduce the informed traders' advantage. Likewise, he provides empirical predictions on the effect of the signal content: a more surprising public announcement would lead to higher volume as liquidity traders rebalance their portfolios but it would not affect price impact. Instead of focusing on homogeneous informed traders, Pasquariello and Vega (2007) considers a model with heterogeneously informed traders and show that the public signal's realization leads to higher market liquidity. In a similar vein, Kandel and Pearson (1995) develops a model in which traders agree to disagree, and they disagree more after the public signal. As a consequence volume and expected gains from trade increase.

Table 1 compiles the predictions of each alternative mechanism to guide the analysis. The main empirical prediction of the proposed model is the independence between the effect on spreads and volume and the content of the announcement, which differentiates the model from previous ones. Additionally, the effect on market quality distinguishes the endogenous participation and the disagreement or disclosure channels. While the former predicts a liquidity deterioration, the latter have the opposite prediction.

[Table 1 about here.]

This paper also relates to a broader theoretical literature by constructing a model à la Glosten and Milgrom (1985) with a public signal and risk averse informed traders.[3] Regarding risk aversion, Holden and Subrahmanyam (1994) introduces risk averse informed traders in Kyle (1985)'s model, but they do not consider public news. In a different vein, inventory models such as Ho and Stoll (1981), Madhavan and Smidt (1991), Hendershott and Menkveld (2014) and references therein, consider a risk averse market maker. These papers, however, abstract from information asymmetries. To my knowledge, only the complementary model of Sastry and Thompson (2018) includes a public signal in an information based dynamic model. While they characterize the behavior of traders in a very general information setting, I focus on a unique public signal and flexible preferences. Technically, both models would need to be solved numerically but the the propositions relevant for the empirical exercise can be obtained analytically in the model I propose. The lack of an analytical solution derives directly from the endogenous composition of traders, which makes the market maker's learning process depend on the whole order history.

[3] O'Hara (1995) reviews the seminal information based models.

Regarding the empirical contribution, the purpose of my paper is to analyze the effect of a public announcement on liquidity conditional on the actual data announced. This feature is missing in the existing literature on the effect of public news on asset markets.[4] However, Brown, Hillegeist, and Lo (2009) and Riordan, Storkenmaier, Wagener, and Zhang (2013) already take a step in this direction by conditioning on the sign of the data. The former shows that positive earning surprises decrease information asymmetry with respect to zero-surprise announcements, whereas bad surprises increase it. Likewise, Riordan, Storkenmaier, Wagener, and Zhang (2013) identifies that the adverse selection problem worsens after Reuters releases some information, especially if it conveys negative news.

Besides considering the continuous realization of the signal, there are several differences between my study and the previous ones due to the nature of the public announcement and the empirical strategy. For instance, bad news and negative earnings surprises are more prevalent in times when uncertainty is higher (crises periods), therefore, results might be driven by changes in uncertainty instead of being a consequence of the news' content. Using a difference-in-differences methodology and month-year fixed effects, I tackle this concern. Another issue is the endogeneity that arises because journalists and CFOs select what to publish. While a CEO diverting money to her account might cover the front page of financial newspapers, we do not read the opposite information every day. In this regard, the institutional setup of the WPS report solves this problem since it is released by a governmental agency in a mechanical fashion.

The introduction follows the order in which the paper was created: testing the prevailing channel, proposing a new mechanism, and finally testing it. However, to ease

[4] While previous research does not study the WPS, it analyzes macroeconomic announcements (Ederington and Lee, 1993; Fleming and Remolona, 1999; Green, 2004; Pasquariello and Vega, 2007; Hess, Huang, and Niessen, 2008; Elder, Miao, and Ramchander, 2012), earnings announcements (Beaver, 1968; Ball and Brown, 1968; Foster, Olsen, and Shevlin, 1984; Bernard and Thomas, 1989, 1990; Lee, Mucklow, and Ready, 1993; Krinsky and Lee, 1996; Vega, 2006; Savor and Wilson, 2016), and news feeds (Liu, Smith, and Syed, 1990; Barber and Loeffler, 1993; Berry and Howe, 1994; Chan, 2003; Antweiler and Frank, 2004; Chae, 2005; Ranaldo, 2005; Tetlock, 2010). Nonetheless, these papers abstract from the effect of the signal content on liquidity.

the exposition, the rest of the paper follows a different order. First, the next section outlines the model and derives its empirical predictions. Then, I describe the institutional setting and the data in Section 2. Finally, I present the empirical results in Section 3 and conclude.

1. Model

Consider a market in which a unique asset can be traded at T different periods in time. The liquidation value of the asset equals the sum of three independent components: $v = \omega + \mu + \varepsilon$. The first one, ω, is subject to an asymmetric information problem, because some traders know it from the first period ($t = 0$) while the remaining agents only know that ω can take two values: σ_ω with probability $\frac{1}{2}$ and $-\sigma_\omega$ otherwise. On the other hand, no trader knows μ before the public signal is released ($t = t_R$), and everyone does afterward. Finally, the third component, ε, represents the part of the asset value that is only known at liquidation. Without loss of generality, I assume that μ and ε have an expectation equal to zero and a variance equal to σ_μ and σ_ε respectively.

There are two types of traders in the market: a mass $1 - \delta$ of noise traders who buy and sell randomly with probability $\dfrac{1}{2}$, and a mass δ of informed traders who know the realization of ω and maximize their expected utility. At each time t, one random trader buys, sells or does not trade, and she dies.[5] While for some not very liquid stocks, strategic behavior might be important; in the case of highly liquid stocks, describing traders as price takers is not a farfetched assumption. Additionally, hereafter, I assume that both types of agents exist in the market ($0 < \delta < 1$).

Contrary to previous literature, informed agents are risk averse. Specifically, informed agents' utility is given by $U(d_i) = \left(\mathbb{E}\left(v|\omega\right) - p\left(d_i\right)\right) d_i - \gamma_i Var\left(v|\omega\right) |d_i|$ where $d_i = 1$ ($d_i = -1$) if they buy (sell) and $d_i = 0$ if they do not take any action; and $p(1)$ is the ask price while $p(-1)$ denotes the bid price. Note that, as it is common in the

[5] This assumption is common to previous literature (see Glosten and Milgrom, 1985; Easley and O'Hara, 1987, and references thereafter)

literature, informed investors trade, at most, one unit.[6] Additionally, informed investors are heterogeneous in their risk aversion since γ is randomly distributed with c.d.f $F(\cdot)$. To ease the exposition, I assume that $F(\cdot)$ is differentiable and strictly increasing with support equal to $\mathbb{R}^+$. Direct evidence on informed investors' preferences is unachievable, nonetheless, using a structural model, Koijen (2014) estimates a risk aversion coefficient equal to 5.75 with a standard deviation of 10.53 which supports the heterogeneity in risk aversion. Likewise, insiders, or other proprietary traders, invest using their own money; thus, they are likely to act as risk averse agents. Besides, differences in capital, leverage, or nonfinancial characteristics can create heterogeneity in their attitude towards risk.

There is a third type of agent, a competitive market maker, who sets the ask and bid price (A and B respectively) to make zero profits in expectation. This characterization of the market maker as a risk neutral agent can be justified by competition under mild assumptions.

Following Glosten and Milgrom (1985), agents in the market are born at the beginning of each of the T periods knowing the whole sequence of past transactions and prices, and ω if they are informed, and they die at the end. The timing within a period is as follows: first, and only in period t_R, the public information is revealed. Second, the market maker posts an ask and a bid price. Finally, a trader arrives at the market and buys, sells or leaves. Afterward, the next period starts.

Aside from the existence of public news, the setup of the model closely relates to Glosten and Milgrom (1985) and Easley, Kiefer, and O'Hara (1997). Specifically, if $\gamma_i = 0\ \forall i$ the model is the same as Glosten and Milgrom (1985)'s model. On the other hand, if $\gamma_i = 0\ \forall i$ with probability α and $\gamma_i \to \infty\ \forall i$ with probability $1-\alpha$; the model becomes equivalent to Easley, Kiefer, and O'Hara (1997)'s model. To illustrate how this small change affects the model conclusions, I first present the agents' best responses without the release of public news; and then, I consider the case in which μ is revealed.

[6] An exception is the model proposed by Easley and O'Hara (1987) which allows for big and small trades.

1.1. Best responses without public news

Since every informed investor receives the same signal, in equilibrium, their best response does not depend on past quotes and transactions. Instead, they take current quotes as given and maximize their utility conditional on ω. As a result, their reaction function is given by:[7]

$$d_i^*(A,B) = \begin{cases} 1 & \text{if } \gamma_i < \dfrac{\omega - A}{\sigma_\mu + \sigma_\varepsilon} \\ -1 & \text{if } \gamma_i < \dfrac{B - \omega}{\sigma_\mu + \sigma_\varepsilon} \\ 0 & \text{otherwise} \end{cases}$$

Informed investors buy if their information rents, $\omega - A$, cover their disutility from risk, $\gamma_i (\sigma_\mu + \sigma_\varepsilon)$. Therefore, the participation of informed traders highly depends on the quotes. If bid and ask prices are high, informed investors are less likely to buy; thus, buys do not carry much information. On the other hand, lack of trades and sales provide much more information as they are more likely to be from an informed trader.

Meanwhile, the market maker sets a bid and ask price to break even in expectation, conditional on the whole sequence of transactions up to time t. Precisely, her profit function is given by

$$U_t^{MM}(A,B) = \mathbb{E}\left[\mathbb{1}\{d_t = 1\}(v - B) + \mathbb{1}\{d_t = -1\}(A - v)\,|\mathcal{H}_t\right]$$

where $\mathcal{H}_t$ denotes the sequence of transactions up to time t. The assumption of perfect competition implies that equilibrium prices satisfy:

$$A_t^* = -\sigma_\omega + 2\Pi_t^+\,\sigma_\omega, \text{ and } B_t^* = -\sigma_\omega + 2\Pi_t^-\,\sigma_\omega$$

where Π_t^+ (Π_t^-) are the market maker beliefs that $\omega = \sigma_\omega$ conditional on all the trades up to t and a buy (sell) order $d_t = 1$ ($d_t = -1$).[8]

[7] I do not consider the case in which $B > A$, as it does not occur in equilibrium.

[8] To avoid extra notation, I denote by d, the current order (d_t), and the reaction of informed investors (d_i). Along the paper, I use stars to represent equilibrium quantities and actions.

In previous models, the probability of informed trading is constant and symmetric during all trading periods. In my model, however, this probability changes as time passes by, and it is different if we consider the buy or the sell side. To illustrate the dynamics of traders' composition, consider the probability of informed buying, $PIB = \delta F\left(\frac{\sigma_\omega - A_t^*}{\sigma_\mu + \sigma_\epsilon}\right)$. If the true state is $\omega = \sigma_\omega$, the market maker learns through trades and the information rents $(\omega - A_t^*)$ reduce, which on average, leads to a reduction in informed trading. Additionally, at each point in time A_t^* adjusts inducing variation in the PIB.

The absence of symmetry is a direct implication of the endogenous composition of traders and creates two important differences with respect to previous models. First, the lack of trading signals the value of the asset. When prices are close to σ_ω, the information rents from buying are small and most informed traders exit the market without transacting if the value of the asset is high. The market maker internalizes this behavior and raises prices even more. Likewise, the opposite situation happens with low prices. This finding relates to Easley, Kiefer, and O'Hara (1997) which shows that lack of trading can signal the absence of private information. My model takes one step further and proves that it can also signal the sign of this information.

Secondly, the order of trades is important, hence the number of buys and sales is not enough to characterize prices. To exemplify why the order is important, consider the change in prices after a buy followed by a sale and viceversa. In the former situation, the sale takes place when prices are high due to the prior buy, therefore the seller is likely to be an informed trader. In the opposite case, one sale after a buy, the initial decrease in prices is lower than the previous one as prices are lower. The posterior increase, however, is greater by cause of lower prices. As a result, prices after the two transactions are lower in the first case than in the latter.

Finally, note that agents are not forward-looking. Accordingly, the model without public news is equivalent to releasing a public announcement at $T + 1$, after the market closes. Hence, I describe the equilibrium and its properties for the more general case in which there is a public announcement at t_R.

1.2. Equilibrium with public news

An equilibrium in this model is given by the triples $\{d_i^*(A_t^*, B_t^*, \omega), A_t^*(\mathcal{H}_t), B_t^*(\mathcal{H}_t)\}_0^{t_{R-1}}$, and $\{d_i^*(A_t^*, B_t^*, \mu, \omega), A_t^*(\mathcal{H}_t, \mu), B_t^*(\mathcal{H}_t, \mu)\}_{t_R}^{T}$ where d_i^* is the informed agents' best response and the market maker obtains zero profits in expectation with quotes equal to A^*, and B^*. Importantly, quotes depend on the whole sequence of transactions ($\mathcal{H}_t$). Proposition 1 describes the equilibrium prices and strategies. Additionally, Corollary 1 shows that the spread is always positive, and informed traders do not trade against their information.

Proposition 1. *An equilibrium exists and it is unique. Moreover, it is given by:*

If $t < t_R$,

$$d_i^*(A^*, B^*, \omega) = \begin{cases} 1 & \text{if } \gamma_i < \dfrac{\omega - A^*}{\sigma_\mu + \sigma_\varepsilon} \\ -1 & \text{if } \gamma_i < \dfrac{B^* - \omega}{\sigma_\mu + \sigma_\varepsilon} \\ 0 & \text{otherwise} \end{cases}$$

$$A_t^* = -\sigma_\omega + 2\frac{\frac{1}{2}(1-\delta) + F\left(\dfrac{\sigma_\omega - A_t^*}{\sigma_\mu + \sigma_\varepsilon}\right)}{\frac{1}{2}(1-\delta) + \Pi_t F\left(\dfrac{\sigma_\omega - A_t^*}{\sigma_\mu + \sigma_\varepsilon}\right)}\Pi_t\, \sigma_\omega$$

$$B_t^* = -\sigma_\omega + \frac{(1-\delta)}{\frac{1}{2}(1-\delta) + (1-\Pi_t)F\left(\dfrac{B_t^* + \sigma_\omega}{\sigma_\mu + \sigma_\varepsilon}\right)}\Pi_t\, \sigma_\omega$$

If $t \geq t_R$,

$$d_i^*(A^*, B^*, \mu, \omega) = \begin{cases} 1 & \textit{if } \gamma_i < \dfrac{\mu + \omega - A^*}{\sigma_\varepsilon} \\ -1 & \textit{if } \gamma_i < \dfrac{B^* - \mu - \omega}{\sigma_\varepsilon} \\ 0 & \textit{otherwise} \end{cases}$$

$$A_t^* = \mu - \sigma_\omega + 2\frac{\frac{1}{2}(1-\delta) + F\left(\dfrac{\mu + \sigma_\omega - A_t^*}{\sigma_\varepsilon}\right)}{\frac{1}{2}(1-\delta) + \Pi_t F\left(\dfrac{\mu + \sigma_\omega - A_t^*}{\sigma_\varepsilon}\right)} \Pi_t \, \sigma_\omega$$

$$B_t^* = \mu - \sigma_\omega + \frac{(1-\delta)}{\frac{1}{2}(1-\delta) + (1-\Pi_t) F\left(\dfrac{B_t^* - \mu + \sigma_\omega}{\sigma_\varepsilon}\right)} \Pi_t \, \sigma_\omega$$

where Π_t *are the market maker beliefs that* $\omega = \sigma_\omega$ *conditional on all the trades up to* t*.*

Corollary 1.

$$\sigma_\omega > A_t^* > B_t^* > -\sigma_\omega \textit{ if } t < t_R \textit{ and } \mu + \sigma_\omega > A_t^* > B_t^* > \mu - \sigma_\omega \textit{ if } t \geq t_R.$$

Proofs of the theoretical results are gathered in Appendix A.

Endogenous participation generates two effects when the market maker increases the spreads. First, she earns higher profits because of the higher price. Second, her profits increase because some informed agents leave the market. The latter effect is the contribution of this model and it plays an important role when the public news is published. At that point in time, the uncertainty about the asset value reduces, and more informed traders participate. Therefore, the order flow becomes more informative which forces the market maker to charge a wider spread.

In terms of comparative statics, for a given sequence $\mathcal{H}_t$, a higher private information volatility, σ_ω, generates higher spreads, and higher volume, as information rents are higher. Similarly, an increase in the proportion of informed agents δ leads to a rise in the spreads but decreases volume since noise traders always transact. Instead, an increment of σ_ε

decreases spreads and volume since informed agents are less likely to participate.

1.3. Model predictions

Since the empirical part relies on a difference-in-differences methodology, to create proper hypotheses, I compare the model predictions if there is no public news (labeled with a subscript 0) against the predictions with public news (labeled with subscript 1), keeping the realized variables constant.

Figure 1 sketches the main mechanism of the model if $\omega = \sigma_\omega$ and $d_{t_R-1} = -1$. Before the time of release, informed agents whose risk aversion coefficient is above $\underline{\gamma}$ leave the market without trading, regardless if μ will be revealed or not. At t_R the two models differ. If a public signal does not exist, then the market maker decreases the ask price because, after observing a sale ($d_{tR} = -1$), she updates negatively her beliefs about ω. This price movement increases the informational rents, thus fosters informed participation and every trader with risk aversion below $\hat{\gamma}$ buys. If traders observe μ, we have an additional effect; the risk that informed traders face decreases which leads to even a more informative order flow. As a consequence, adverse selection costs rise which leads the market maker to set a wider spread, thus diminishing the profits of informed agents. Nonetheless, in equilibrium every investor below $\overline{\gamma} > \hat{\gamma}$ participates in the market.[9] The boost in participation creates a complementarity between public and private news; specifically, introducing a public signal increases the speed at which private information is incorporated into prices.

[Figure 1 about here.]

Along the paper, I consider three different variables that I observe in the data: midpoint returns, bid-ask spread, and volume. The first one is a measure about price dynamics and is defined as $m_t - m_{t-1}$ where $m_t = \frac{A_t+B_t}{2}$. Proposition 2 characterizes the dynamics of m_t in both scenarios, with and without public news. Consistent with the semistrong market hypothesis, the midpoint rises by μ as soon as the public information

[9]The order of the different thresholds is a direct result of Proposition 3

is disclosed and remains constant afterward. In contrast, risk aversion and asymmetric information do not have any effect on the midpoint.

Proposition 2. *(Midpoint) In equilibrium, the expected midpoint is given by:*

$$\mathbb{E}_{\mathcal{H}_t}(m^*_{1t}) = \mathbb{E}_{\mathcal{H}_t}(m^*_{0t}) = 0 \text{ } if \text{ } t < t_R$$

$$\mathbb{E}_{\mathcal{H}_t}(m^*_{1t}) = \mu \text{ } and \text{ } \mathbb{E}_{\mathcal{H}_t}(m^*_{0t}) = 0 \text{ } if \text{ } t \geq t_R$$

The second variable I consider is the bid-ask spread, which is defined as $A_t - B_t$. Intuitively, it is a buffer the market maker needs to have to maintain zero profits under the presence of informed investors. Proposition 3 states that as soon as μ becomes common knowledge, the bid-ask spread increases, moreover, this rise is independent of μ as it is a result of a composition effect. If informed investors do not know μ they are less willing to act on their information since it entails a high risk. Once they observe μ these investors start trading. To maintain zero profits in expectation, the market maker reacts widening the spread. After the release of the signal, the market maker learns quicker about ω from trades since more informed traders participate. Hence, the bid-ask spread decreases and converges to the one in the model without news.

Proposition 3. *(Bid-ask spread) At the release time, $t = t_R$, the bid-ask spread satisfies:*

$$A^*_{1,t_R} - B^*_{1,t_R} > A^*_{0,t_R} - B^*_{0,t_R}$$

Moreover, the difference $A^*_{1,t_R} - B^*_{1,t_R} - (A^*_{0,t_R} - B^*_{0,t_R})$, does not depend on μ. Additionally, in the limit, the spread in both scenarios converges. Precisely,

$$lim_{T\to\infty} A^*_{1,T} - B^*_{1,T} = lim_{T\to\infty} A^*_{0,T} - B^*_{0,T} = 0 \tag{1}$$

The last variable I analyze is volume, $\mathbb{E}(|d_t|)$, which is a relevant measure of liquidity. Proposition 4 specifies that volume increases at t_R and this effect decreases as the gains from trade decrease. Similar to spreads, the signal content does not affect the increment at the time of the release, nor the dynamics afterward.

Proposition 4. *(Volume) When the public information is released, volume on the days with news is higher than the days without news:*

$$\mathbb{E}\left(|d^*_{1,t_R}|\right) > \mathbb{E}\left(|d^*_{0,t_R}|\right)$$

Further, the difference does not depend on μ. Moreover, it disappears in the limit:

$$lim_{T\to\infty}\mathbb{E}\left(|d^*_{1,T}|\right) = lim_{T\to\infty}\mathbb{E}\left(|d^*_{0,T}|\right) = (1-\delta) \tag{2}$$

2. Institutional framework and data

Every Wednesday at 10:30 a.m., the Energy Information Administration posts the Weekly Petroleum Status Report which contains information about the stock of oil stored in the US by geographical area and product (crude, gasoline, etc.). The report contains a press note highlighting the main figures: oil refined, imports and oil inventories, a table that summarizes the data, and several spreadsheets which contain the disaggregated information. All these documents are available online and they are easily machine readable as the format is constant across weeks.

The information in the report is the official and the only public data available. However, there are private companies that provide some data on inventories before Wednesdays. For instance, a data service company relies on drones to measure the amount of stock inside the tanks and provide the information to its clients on Mondays at 10:00 a.m. While this information might be valuable, the official report remains the main driver of oil price movements during trading hours. To see this, I plot in Figure 2 the percentage of the weekly intraday variance of the nearest-to-maturity oil future for each minute and weekday. In line with the previous statement, the maximum intraday variance is concentrated on the exact time of the report release. In fact, the pattern is mainly flat across days and minutes except on Wednesday at 10:30 a.m, and the closing of the open outcry at Chicago Mercantile Exchange at 2:30 p.m.

[Figure 2 about here.]

Aside from the current oil stock level, the Energy Information Administration also makes the historical ones available which constitute the first source of data in the paper. From the reports, I use the weekly differences in the total stock of oil, excluding the strategic petroleum reserve, to quantify the information that the public news convey. Note that the choice of oil product and location is irrelevant for the results since all of them are close substitutes; thus, their inventories are highly correlated. At the same time, an ideal measure of news should not include the information previously known. Thus, I extract the unpredictable component of the increase in inventories by subtracting the median forecast provided in Bloomberg ($\widetilde{\Delta Inv}$) to the reported change in inventory (ΔInv). Then, I normalize the forecast error to have a standard deviation equal to one and a sample average equal to zero:

$$News_t = \frac{\Delta Inv_t - \widetilde{\Delta Inv_t} - \left(\frac{1}{T}\sum_{t=1}^{T}\left(\Delta Inv_t - \widetilde{\Delta Inv_t}\right)\right)}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\Delta Inv_t - \widetilde{\Delta Inv_t}\right)^2}}$$

Supplementary to these data, the effect of the report should be very different on industries that highly depend on oil versus those which do not; therefore, it is important to differentiate these two groups. To classify firms as oil or nonoil, I obtain how many dollars of this commodity a particular industry requires to produce one dollar of total output using the Bureau of Economic Analysis Input-Output tables from 1999. In general, industries require between three and ten cents of oil; hence I define oil firms as those in an industry that needs more than 0.2$. In my main sample there are two industries that fulfill this criterion: oil extraction firms (0.76$) and refineries (0.38$). Consequently, those make up my definition of the oil sector.

Lastly, I construct market variables from the Trade and Quote data set which includes each transaction price and size, as well as the best bid and ask quotes. My available sample includes data on 50 randomly chosen firms, stratified in two volume buckets according to the data on CRSP at 2005, from January 2007 to June 2013. Regarding data processing, I apply the filters proposed by Holden and Jacobsen (2014), I aggregate the variables inside a minute, and I winsorize every variable at the 1% in each minute. As a result, each observation in my data set is a minute inside a given day for a specific firm. Additionally, I drop from the sample minutes without transactions to avoid stale quotes.[10]

From the final sample, I construct three main variables: midpoint returns, proportional effective bid-ask spread, and volume. The midpoint return measures changes in the mean beliefs about the value of the asset and is defined as: $r_t = log(\bar{m}_t) - log(\bar{m}_{t-1})$, where $\bar{m}_t = \frac{1}{K_t}\sum_\tau \frac{A_\tau + B_\tau}{2}$, A_τ and B_τ are the ask and bid prices posted at the time of transaction τ, and K_t is the total number of transactions in minute t. The second variable I analyze, the spread, is an indicator of transaction costs and has been associated with the degree of information asymmetry (see Glosten and Milgrom, 1985). I construct it as $sp_t = \frac{1}{K_t}\sum_\tau |\frac{p_\tau - m_\tau}{m_\tau}|$ where p_τ is the actual transaction price. The final variable I consider is volume, which reflects market activity, as it consists of the number of shares traded in a minute.

These variables match the variables considered in the theoretical framework in Propositions 2, 3, and 4. Additionally, through the lenses of the model, $News$ is similar to μ, t_R corresponds to 10:30 a.m. and ω represents private information that some traders have related to oil prices. In my setup private information can be thought as insiders who receive some private signal; but it can also be understood as investment companies or departments who process information, such as the worldwide weather, better than most investors. Finally, following Easley, Kiefer, and O'Hara (1997), I interpret that the model represents a day, and at the beginning of each day, the game

[10] Results are robust to include nontrading minutes and use quoted instead of effective spread, and volume instead of the logarithm of volume.

starts again. Therefore, the difference between Wednesdays and any other day of the week equals the difference between the model with and without public news, if everything else is constant.

3. Empirical analysis

I test the model hypotheses using a difference-in-differences approach. I consider oil firms as treated and nonoil firms as the control group. At the same time, I compare Wednesdays with the other weekdays. To be precise, I estimate the following equation,

$$y_{i,t} = \mu + \delta_m + \theta_0 Oil_i + \theta_1 News_t + \theta_2 Wed_t + \theta_3 Wed_t \cdot News_t + (\gamma_0 News_t + \gamma_1 Wed_t + \gamma_2 Wed_t \cdot News_t) \cdot Oil_i + \varepsilon_{i,t} \quad (3)$$

where $y_{i,t}$ is the value of the variable of interest for firm i on day t, δ_m are month-year fixed effects, and Oil_i and Wed_t are dummy variables that indicate if the firm belongs to the oil sector and if the day of the week is Wednesday. To characterize the complete dynamics, I estimate Equation (3) for every minute independently. Hence, observations are at the daily-firm level. Since $News$ varies on a weekly basis, and to account for some correlation across weeks, I cluster standard errors at the monthly level.

To identify the effect of the presence of a public announcement, I make three main assumptions: First, nonoil firms are not affected by the oil report. Second, the presence of the report publication only affects Wednesdays, and third, there is no other factor that affects differently oil and nonoil firms at 10:30 a.m. on Wednesdays. The supplemental appendix provides evidence in favor of these assumptions. Table S.28 shows that the results are qualitatively similar but more pronounced if we compare an oil ETF with a gold ETF. As regards to the control period, Section S.4 compares Wednesdays with each of the other weekdays separately, and results are unaltered regardless of the weekday used as a control. Finally, Section S.14 addresses the issue of an omitted factor by conducting a difference-in-difference-in-differences where the third difference corresponds to the change before and after the EIA started publishing the report on Wednesdays at 10:30 a.m. and the same results prevail.

The key parameters of interest are γ_1 and γ_2. While the first one captures the effect irrespective of the news, the second one measures the reaction to the report's content. To focus the attention on the release, I restrict the sample to the period from 10:00 a.m. to 10:59 a.m. I refer to parameters from different minutes with a superscript. For instance, $\gamma_1^{10:00}$ is the estimate of γ_1 using only data at 10:00 a.m. and variation across days and firms.

The theoretical results state that prices should react instantaneously in the direction of public information. Since a decrease in inventories implies a high μ in terms of the model, the empirical hypothesis is that $\gamma_2^{10:30} < 0$. At any other time different from the release time, the model predicts that price dynamics are equal with and without news; equivalently, $\gamma_2^m = 0$ for every m except $m =$ 10:30. In the upper plot of Figure 3 I depict the estimates of γ_2 and their 95% confidence intervals. They confirm the previous hypotheses. Precisely, prices rise immediately by 5.4 bps if inventories drop by one standard deviation, but they remain constant afterward. Meanwhile, the lower plot depicts the estimates of γ_1. Consistent with the model prediction, the disclosure of a public signal is irrelevant besides its content; equivalently, if the report does not provide new data, $\mu = 0$, prices do not react.

[Figure 3 about here.]

Apart from the empirical support to the proposed model, these results support the assumption that informed investors lack prior information about oil stocks. Otherwise, these investors would buy before upcoming news of a decrease which would push prices up as the market maker learns from the fundamental. This mechanism creates a negative correlation between the unexpected change in inventories and returns prior to the release that is not consistent with the data.

Regarding the spread, the model predicts an increase after the release, independently on the information content. Since liquidity providers quote prices in advance, we expect the effect on spreads to be just before 10:30 a.m ($\gamma_1^{10:29} > 0$). Moreover, this effect lasts for some periods as the market maker learns about the private signal although, it finally vanishes. Therefore, I hypothesize that $\gamma_1^m > 0$ if $m \geq$ 10:29 but $\gamma_1^m = 0$ if $m <$ 10:29, or $m \gg$ 10:30. The duration of the effect depends on the parameters of the model. The upper plot of Figure 4 shows that the spread increases at 10:29 a.m. by 2.78 bps and it slowly decreases, and it becomes insignificant after thirty minutes. At the same time, in line with the model, the lower plot confirms that unexpected change in inventories is irrelevant for the spread.

[Figure 4 about here.]

The increase of spreads is inconsistent with models that hinge on disagreement and those that consider the public signal as a substitute of the private signal. Nevertheless, models that consider private and public signals as complements accommodate this empirical finding. To test the endogenous participation mechanism against this type of models, I estimate the effect of the announcement on volume. In particular, models à la Kim and Verrecchia (1991) predict a tight link between volume movements and the information content ($\gamma_1^{10:30} = 0$ and $\gamma_2^{10:30} > 0$) whereas my mechanism generates the opposite prediction ($\gamma_1^{10:30} > 0$ and $\gamma_2^{10:30} = 0$). Both channels lead to a persistent, although not permanent, effect.

Figure 5 present the estimates of Equation (3) with volume as a dependent variable. We observe a similar pattern to the one in the analogous figure for the spread (Figure 4). Precisely, volume rises by 32% at the moment of the announcement and it decreases afterward. In addition, the presence of news barely affects market activity before its release. There is a statistically significant decrease in volume just before the release but its magnitude is economically small as it implies a 0.04% volume decrease on average. This mild prior reaction suggests that traders neither know the information before nor do they strategically defer their trading. Regarding the report's information, it does not affect the increment in volume, or the posterior dynamics, as the proposed model suggests, but in contrast to alternative models.

[Figure 5 about here.]

Lastly, the model predicts that the case with a release, eventually, converges to the one without news. I show that this convergence is immediate as regards returns, but it takes some minutes in terms of volume and spreads in line with the model. Indeed, at the end of the day, we observe no significant difference between days with and without public news.

The supplemental appendix includes several additional tests to confirm that results are robust to considering asymmetric or nonlinear reactions to news, controlling for the level of disagreement, comparing Wednesdays with each one of the other weekdays, including minutes without trading, conditioning on the actual raw change of inventories instead of the surprise, and incorporating every oil firm independently.

3.1. The effect of magnitude

The theoretical model concludes that the effect on spreads and volume should be independent to the new information in the report. However, the previous results just control for the change in inventory; instead, the absolute value of the public signal might be the relevant variable as Kim and Verrecchia (1994)'s model predicts. To explore this alternative channel, I estimate the following model:

$$y_{i,t} = \mu + \delta_t + \theta_0 Oil_i + \theta_1 \left|News_t\right| + \theta_2 Wed_t + \theta_3 Wed_t \cdot \left|News_t\right| + \\ \left(\gamma_0 \left|News_t\right| + \gamma_1 Wed_t + \gamma_2 Wed_t \cdot \left|News_t\right|\right) \cdot Oil_i + \varepsilon_{i,t}. \quad (4)$$

Fixed effects are important in this specification as we have two opposite effects. On the one hand, periods with volatile changes in inventory (high σ_μ) should present bigger effects according to the model. On the other hand, if the model parameters are fixed, the absolute unexpected change in inventories should be irrelevant. By the use of month-year dummies, I control for variability at a low frequency. Hence, we can interpret the other coefficients as if the parameters of the model do not vary. Therefore, according to the model, $\gamma_2^m = 0$ for all m, and the estimate of γ_1 should not change with respect to the same coefficients in equation (3). Figure 6 shows that this coefficient does not change for any of the three market variables. Besides, the absolute value of inventories does not have an effect on the market.

[Figure 6 about here.]

3.2. Relevance of the public signal

Although the model predicts the same increase in volume and spreads regardless of the realization of the signal, it predicts a stronger effect when the public signal provides more information (higher σ_μ). Therefore, spreads and volume after an important inventory announcement should rise more than after a less relevant one, even if the content of the report is exactly the same. To estimate σ_μ, I rely on the ex-ante measure proposed by Dubinsky, Johannes, Kaeck, and Seeger (2019) in the context of earnings announcements. Using the same model, we can obtain a slightly different formula that accounts for the frequency of announcements:

$$\widehat{\sigma_\mu} = \frac{IV_{t,T_1}^2 - IV_{t,T_2}^2}{M_{t,T_1}(T_1 - t)^{-1} - M_{t,T_2}(T_2 - t)^{-1}}, \ (T_1 < T_2)$$

where IV is the implied volatility, t indexes time, and T_i is the maturity of the option i. $M_{t,T} > 0$ is the number of oil inventory announcements from t to T. In the original paper, $M = 1$ as it is possible to find two options with different maturities and the same number of earnings announcements in between. However, due to the weekly frequency of the inventory release, the number of Weekly Petroleum Status Reports between two maturities is always different.

I extract the daily price of every option from OptionMetrics from January 2005 to December 2017. I follow Bakshi, Kapadia, and Madan (2003) to compute the implied volatility per firm, day and maturity as a weighted average of option premiums across strikes. As suggested in Dubinsky, Johannes, Kaeck, and Seeger (2019), for a given day and firm, I consider the two shortest maturities as long as they expire in more than seven days. Then, I aggregate every day in between two successive reports and across oil firms to obtain a relevance measure at the weekly level.

Panel A of Table 2 provides the estimation results from an extension of equation (3):

$$\begin{aligned} y_{i,t} = \mu + \delta_m + \theta_0 Oil_i + \theta_1 News_t + \theta_2 Wed_t + \theta_3 Wed_t \cdot News_t + \\ (\gamma_0 News_t + \gamma_1 Wed_t + \gamma_2 Wed_t \cdot News_t) \cdot Oil_i + \\ \left(\theta_0^H Oil_i + \theta_1^H News_t + \theta_2^H Wed_t + \theta_3^H Wed_t \cdot News_t\right) \cdot \widehat{\sigma_{\mu,t}} + \\ \left(\left(\gamma_0^H News_t + \gamma_1^H Wed_t + \gamma_2^H Wed_t \cdot News_t\right) \cdot Oil_i\right) \cdot \widehat{\sigma_{\mu,t}} + \varepsilon_{i,t} \end{aligned} \quad (5)$$

where $\widehat{\sigma_{\mu,t}}$ is the relevance measure standardized to have standard deviation equal to one. The first column shows that prices move according to the unexpected change in inventory and the reaction does not depend significantly on the ex-ante relevance of the announcement. This finding suggests that the volatility of the unexpected change in inventory drives the relevance of the signal, as opposed to the volatility of firms' reaction to these data. The second and third columns show that spread and volume increase independently of the report content and the effect is stronger after important reports, in line with the model. Precisely, an increase of one-standard deviation in the signal relevance augments the effect by around a third. Finally, Panel B ensures that the same results hold if we substitute the unexpected change in inventories by its absolute value.

[Table 2 about here.]

3.3. *Implied volatility*

The main mechanism of the model relies on a decrease in the volatility of oil stocks. Although the change in prices indicates that investors learn about the fundamental value of the stocks, their perceived volatility might not decline or its dynamics might depend on the report's content. To provide some additional evidence about changes in volatility, I estimate the following equation:

$$log(IV)_{i,t,\tau} = \mu + \delta_m + \theta_0 Oil_i + \theta_1 News_t + \lambda_1 Mat_\tau + \lambda_2 Mat_\tau^2 + \theta_2 AW_t + \theta_3 AW_t \cdot News_t + (\gamma_0 News_t + \gamma_1 AW_t + \gamma_2 AW_t \cdot News_t) \cdot Oil_i + \varepsilon_{i,t} \quad (6)$$

where i indexes firms, t days and τ maturities. There are two main differences with respect to the baseline specification. First, the estimation relies on the validity of the difference-in-differences methodology during the whole week, instead of doing it by the minute. Second, the report reduces the volatility on Wednesdays but it would remain fairly constant until the end of the week, therefore I substitute the Wednesday's dummy for a dummy that indicates if the day is Wednesday, Thursday or Friday (AW_t). As a consequence, the post-event period contains options with lower maturity which would be problematic if the term structure of implied volatility is not flat. To tackle this concern, I control for the option's maturity through a second-order polynomial (Mat_τ and Mat_τ^2). Altogether, the main assumption is that conditional on maturity, the difference in implied volatility between oil and nonoil firms would be the same in the first and second half of the week in the absence of the report. This assumption is much stronger than the ones in the baseline specification and results should be interpreted as suggestive, rather than causal, evidence.

Panel A of Table 3 presents the results using three different measures of implied volatility. The first one is the average implied volatility provided by OptionMetrics, which relies on the binomial model, while the second and the third one correspond to the modelfree implied volatility measures proposed by Demeterfi, Derman, Kamal, and Zou (1999) and Bakshi, Kapadia, and Madan (2003), respectively. Across different measures, the estimates are consistent with the model predictions: implied volatility decreases around 0.5% and this decrease does not depend on the announcement.

[Table 3 about here.]

3.4. Insider trading

The mechanism of the model links the reduction in variance to liquidity and prices through the participation of informed traders. Unfortunately, data on specific traders is not available and finding empirical evidence on changes in the pool of traders is not possible. The only exception are insiders, who must report their trades expost to the SEC and have been classified as informed traders (e.g. Cohen et al., 2012). Using daily data from the SEC, I estimate the additional insider volume that oil firms have on Wednesday by means of the following regression:

$$
\begin{aligned}
y_{i,t} = \mu + \delta_m + \theta_0 Oil_i + \theta_1 News_t + \theta_2 Wed_t + \theta_3 Wed_t \cdot News_t + \\
(\gamma_0 News_t + \gamma_1 Wed_t + \gamma_2 Wed_t \cdot News_t) \cdot Oil_i + \varepsilon_{i,t} \quad (7)
\end{aligned}
$$

where $y_{i,t}$ is the logarithm of net shares traded by insiders of firm i at date t. The first column of Panel B of Table 3 indicates that insider traders of oil firms participate 16% more in the market than their nonoil counterparts controlling for their differences the remaining weekdays. Their is a caveat, though. Insiders do not report the time of the transaction and these trades might take place before or after the announcement.

One alternative explanation is that the report discloses insiders' information and they trade more aggressively just before its release to profit from their informational advantage. This mechanism would imply more informed sales when inventories increase and more buys otherwise. The second column of Panel B presents the estimation results of the same specification but using the proportion of buys, in terms of shares or volume, as a dependent variable. The coefficient corresponding to the heterogeneous effect depending on the inventory (γ_2) is statistically insignificant and economically small. A back-of-the-envelope calculation suggests that the expected effect on the absolute imbalance is $\mathbb{E}(|0.03 \cdot News|) \approx 2.4\%$ and therefore this mechanism cannot explain most of the increase in volume.[11].

Finally, Cohen, Malloy, and Pomorski (2012) shows that transactions of opportunistic insiders, those who do not trade following a pattern, contain more private information. As a robustness check, I repeat the same estimation but I only consider opportunistic traders. The last columns of Panel B show that results are almost unaltered.

4. Conclusions

This paper shows that the release of public information worsens the adverse selection problem if informed investors are risk averse and participation is endogenous. Nonetheless, higher adverse selection costs come with more informative prices through two different channels. On the one hand, the market maker observes the public news and immediately adjust the quotes. On the other hand, the release of information resolves uncertainty and boosts the participation of informed agents which accelerates the market maker's learning about the private information.

The mechanism behind the model generates clear empirical implications that differ from the predictions of previous research; mainly, the signal's content is irrelevant to explain the movement of volume and bid-ask spreads around its release. I corroborate these hypotheses by estimating the causal effect of publishing the weekly change in oil inventories. Specifically, I find that spreads and volume increase regardless of the actual inventories' data whereas the midpoint reacts to this information. In line with the model, volume and spreads remain high for several minutes whereas the midpoint

[11] I assumed News follows a Gaussian distribution; then $\mathbb{E}(|News|) = \sqrt{\frac{2}{\pi}}$

adjusts instantly.

Alternative mechanisms should not be disregarded as their importance differs according to the nature of the public announcement. For instance, understanding earnings announcements might require some knowledge about the firm, therefore Kim and Verrecchia (1994)'s channel becomes the most relevant. On the other hand, press releases disclose privately held information, hence we expect liquidity to improve after their publication consistent with the empirical findings in Tetlock (2010). Finally, there are important public announcements, as those related to macroeconomic or industry indicators, that are mostly unrelated to private information. In these situations, the endogenous participation of traders becomes first-order importance even if the role of other channels is still important, which explains why Pasquariello and Vega (2007) does not find evidence of a liquidity enhancement around macroannouncements, despite other predictions of their model are supported by the data.

The results of this paper have two important implication for policymakers whose objective is to enhance price informativeness. First, public information entails an amplification mechanism which must be taken into account when deciding the investment to compile information. Secondly, adverse selection costs rise, even if every investor obtains the same information from the public signal. Hence, the widening of bid-ask spreads at the time of a public announcement should not be taken as evidence to support a failure of standardization.

A. Proofs

Proof. Proposition 1

Since the market maker problem is symmetric, I focus, first, on the ask side of the market. To shorten the proof I define σ as the residual variance for the informed investors, i.e. $\sigma = \sigma_\mu + \sigma_\varepsilon$ if $t < t_R$ and $\sigma = \sigma_\varepsilon$ otherwise; and, $\tilde{\mu}$ as the public information at time t, $\tilde{\mu} = 0$ before t_R and $\tilde{\mu} = \mu$ afterward. In the case of no news $\tilde{\mu} = 0$ and $\sigma = \sigma_\mu + \sigma_\varepsilon$ for all t.

To show that there is a unique equilibrium, I first show that the market maker's profits are increasing as the ask quote increases. Then I show that for very low quotes she loses money, whereas for very high quotes she earns profits. Hence, there is one, and only one, quote at which she breaks even.

The zero profit condition is given by:

$$A_t^* = \mathbb{E}\left[v|d = 1, \mathcal{H}_t\right] = \tilde{\mu} + \mathbb{E}\left[\omega|d = 1, \mathcal{H}_t\right]$$

where the last equality comes from independence between ω, μ and ε. Using the distribution of ω, we can write the market maker's profits as:

$$g_A(A) \equiv A + \sigma_\omega - P(\omega = \sigma_\omega|d = 1, \mathcal{H}_t)2\sigma_\omega - \tilde{\mu} \tag{8}$$

where $P(\omega = \sigma_\omega|d = 1, \mathcal{H}_t)$ is the probability of being in the high state of ω conditional of some agent buying and all the past information. Using Bayes' rule, this probability equals:

$$P(\omega = \sigma_\omega|d = 1, \mathcal{H}_t) = P(d = 1|\omega = \sigma_\omega, \mathcal{H}_t)\frac{P(\omega = \sigma_\omega|\mathcal{H}_t)}{P(d = 1|\mathcal{H}_t)}$$

Moreover, note that $\mathcal{H}_t$ is irrelevant if we condition on ω, therefore the first term equals

$$P(d = 1|\omega = \sigma_\omega, \mathcal{H}_t) = P(d = 1|\omega = \sigma_\omega) = F\left(\frac{\sigma_\omega + \tilde{\mu} - A_t^*}{\sigma}\right)\delta + \frac{1}{2}\left(1 - \delta\right)$$

which corresponds to the probability that an informed buys given that the asset value is high times the probability that the trader is actually informed plus the complementary probability times the probability that a noise trader buys, one half.

Likewise, the denominator equals the probability that an informed buys, weighted by the probability that the asset value is high, times the likelihood for him to be informed plus the probability that a noise trader buys:

$$P(d=1|\mathcal{H}_t) = P(\omega=\sigma_\omega|\mathcal{H}_t)F\left(\frac{\sigma_\omega+\tilde{\mu}-A_t^*}{\sigma}\right)\delta+\frac{1}{2}(1-\delta)$$

which leads to the following expression for $P(\omega=\sigma_\omega|d=1,\mathcal{H}_t)$:

$$P(\omega=\sigma_\omega|d=1,\mathcal{H}_t) = \frac{P(\omega=\sigma_\omega|\mathcal{H}_t)\left[F\left(\frac{\sigma_\omega+\tilde{\mu}-A_t^*}{\sigma}\right)\delta+\frac{1}{2}(1-\delta)\right]}{P(\omega=\sigma_\omega|\mathcal{H}_t)F\left(\frac{\sigma_\omega+\tilde{\mu}-A_t^*}{\sigma}\right)\delta+\frac{1}{2}(1-\delta)}.$$

Summing and subtracting $(1-P(\omega=\sigma_\omega|\mathcal{H}_t))\dfrac{1}{2}(1-\delta)$ from the numerator we obtain:

$$P(\omega=\sigma_\omega|d=1,\mathcal{H}_t) = 1-\frac{1-P(\omega=\sigma_\omega|\mathcal{H}_t)}{1+2P(\omega=\sigma_\omega|\mathcal{H}_t)\dfrac{\delta}{1-\delta}F\left(\dfrac{\sigma_\omega+\tilde{\mu}-A_t^*}{\sigma}\right)} \tag{9}$$

from which is obvious that $\dfrac{dP(\omega=\sigma_\omega|d=1,\mathcal{H}_t)}{dA_t^*}<0$. This result directly implies that $g_A'(A)>0$.

Using the definition of $g_A(\cdot)$ in (8), we can check that $g_A(\tilde{\mu}-\sigma_\omega)\leq 0$ and $g_A(\tilde{\mu}+\sigma_\omega)\geq 0$. Therefore, an equilibrium exists and it is unique. Moreover,

$$\tilde{\mu}-\sigma_\omega\leq A_t^*\leq\tilde{\mu}+\sigma_\omega \tag{10}$$

The symmetric proof holds for the bid price.

In the case of the bid price, the zero profit condition is:

$$B_t^* = \mathbb{E}\left[v|d=-1,\mathcal{H}_t\right] = \tilde{\mu} + \mathbb{E}\left[\omega|d=-1,\mathcal{H}_t\right]$$

and we can define the profits from buying as:

$$g_B(B) \equiv B + \sigma_\omega - P(\omega=\sigma_\omega|d=-1,\mathcal{H}_t)2\sigma_\omega - \tilde{\mu} \tag{11}$$

where by Bayes rule,

$$P(\omega=\sigma_\omega|d=-1,\mathcal{H}_t) = \frac{\frac{1}{2}(1-\delta)P(\omega=\sigma_\omega|\mathcal{H}_t)}{(1-P(\omega=\sigma_\omega|\mathcal{H}_t))F\left(\frac{B_t^*+\sigma_\omega-\tilde{\mu}}{\sigma}\right)\delta + \frac{1}{2}(1-\delta)} \tag{12}$$

From this expression is straightforward to check that $g_B'(B) > 0 \; \forall \; B$. Finally, substituting B in equation (11), we obtain that $g_B(\tilde{\mu}-\sigma_\omega) \leq 0$ and $g_B(\tilde{\mu}+\sigma_\omega) \geq 0$.

□

Lemma 1. *In equilibrium, under the assumption that* $0 < \delta < 1$ *and* $F(c) > 0 \; \forall c > 0$*,*

$$0 < P(\omega=\sigma_\omega|d=1,\mathcal{H}_t) < 1$$

Proof. According to equation (9), these inequalities hold if $0 < \delta < 1$, $F(c) > 0 \, \forall c$ and $0 < P(\omega=\sigma_\omega|\mathcal{H}_t) < 1$. While the first two hold by assumption, the third one depends on an endogenous quantity that we can obtain in a recursive fashion. Precisely, there are three cases:

- $d_t = 1 \Rightarrow P(\omega=\sigma_\omega|\mathcal{H}_{t+1}) = P(\omega=\sigma_\omega|d=1,\mathcal{H}_t)$
- $d_t = -1 \Rightarrow P(\omega=\sigma_\omega|\mathcal{H}_{t+1}) = P(\omega=\sigma_\omega|d=-1,\mathcal{H}_t)$
- $d_t = 0 \Rightarrow P(\omega=\sigma_\omega|\mathcal{H}_{t+1}) = P(\omega=\sigma_\omega|d=0,\mathcal{H}_t)$

The first two cases are obtained in equation (9) and (12). The third one can be obtained as:

$$P(\omega = \sigma_\omega | d = 0, \mathcal{H}_t) = \frac{1}{1 + \dfrac{1 - P(\omega = \sigma_\omega | \mathcal{H}_t)}{P(\omega = \sigma_\omega | \mathcal{H}_t)} \dfrac{1 - F\left(\dfrac{\sigma_\omega + \tilde{\mu} - A_t^*}{\sigma}\right)}{1 - F\left(\dfrac{B_t^* + \sigma_\omega - \tilde{\mu}}{\sigma}\right)}}$$

In every case, if $0 < P(\omega = \sigma_\omega | d = 1, \mathcal{H}_t) < 1$ then $0 < P(\omega = \sigma_\omega | d = 1, \mathcal{H}_{t+1}) < 1$. Since $P(\omega = \sigma_\omega | \mathcal{H}_0) = \dfrac{1}{2}$, we proved that $0 < P(\omega = \sigma_\omega | \mathcal{H}_t) < 1 \ \forall t$. □

Proof. Corollary 1

Using Lemma 1, is straightforward to show that inequalities in Equation (10) are strictly satisfied. We can follow a similar argument, and show that these inequalities hold for the bid price.

Besides, to show that $B_t^* < A_t^*$, we subtract $g_A(A_t^*)$ and $g_B(B_t^*)$ leading to the following expression:

$$A_t^* - B_t^* = 2\sigma_\omega \left[P(\omega = \sigma_\omega | d = 1, \mathcal{H}_t) - P(\omega = \sigma_\omega | d = -1, \mathcal{H}_t) \right]$$

Therefore the quoted spread is positive if and only if the right-hand side is positive for every A_t^* and B_t^*; equivalently, using Bayes rule, if and only if

$$\frac{P(d = 1 | \omega = \sigma_\omega, \mathcal{H}_t)}{P(d = 1 | \mathcal{H}_t)} > \frac{P(d = -1 | \omega = \sigma_\omega, \mathcal{H}_t)}{P(d = -1 | \mathcal{H}_t)}$$

Inverting both sides, and applying the law of total probability we get:

$$\frac{P(d = -1 | \omega = -\sigma_\omega, \mathcal{H}_t)}{P(d = -1 | \omega = \sigma_\omega, \mathcal{H}_t)} > \frac{P(d = 1 | \omega = -\sigma_\omega, \mathcal{H}_t)}{P(d = 1 | \omega = \sigma_\omega, \mathcal{H}_t)}$$

Finally, if we plug the corresponding values we obtain

$$B_t^* < A_t^* \iff \frac{\left[F\left(\frac{B_t^* + \sigma_\omega - \tilde{\mu}}{\sigma^2}\right)\delta + \frac{1}{2}(1-\delta)\right]}{\left(\frac{1}{2}(1-\delta)\right)} > \frac{\left(\frac{1}{2}(1-\delta)\right)}{\left[F\left(\frac{\sigma_\omega + \tilde{\mu} - A_t^*}{\sigma^2}\right)\delta + \frac{1}{2}(1-\delta)\right]}.$$

This inequality is satisfied due to the assumptions that $\delta > 0$ and $F(c) > 0$ if $c > 0$. $\square$

Proof. Proposition 2

Given $\mathcal{H}_t = \{d_1, ..., d_{t-1}\}$, let me define $-\mathcal{H}_t = \{-d_1, ..., -d_{t-1}\}$. Next, after some algebra we can show that $(A^*(\mathcal{H}_t) - \tilde{\mu}) = -(B^*(-\mathcal{H}_t) - \tilde{\mu})$. This result implies that:

$$m_t(\mathcal{H}_t) = \frac{A^*(\mathcal{H}_t) + B^*(\mathcal{H}_t)}{2} = -\frac{A^*(-\mathcal{H}_t) + B^*(-\mathcal{H}_t)}{2} = -m_t(-\mathcal{H}_t)$$

Moreover, note that given the symmetry in the model, $P(\mathcal{H}_t|\omega = \sigma_\omega) = P(-\mathcal{H}_t|\omega = -\sigma_\omega)$. Therefore, $\mathbb{E}_{\mathcal{H}_t}(m_{1t}) = \tilde{\mu}$ if there are news; and $\mathbb{E}_{\mathcal{H}_t}(m_{0t}) = 0$, otherwise.

$\square$

Lemma 2.

$$lim_{T\to\infty} A_T = lim_{T\to\infty} B_T = \omega + \tilde{\mu}$$

Proof. The martingale convergence theorem and independence between μ and ω imply

$$lim_{T\to\infty} A_T = lim_{T\to\infty} B_T = \mathbb{E}(\omega|\mathcal{H}_\infty) + \tilde{\mu} \tag{13}$$

where $\mathbb{E}(\omega|\mathcal{H}_\infty)$ is constant. We can prove $\mathbb{E}(\omega|\mathcal{H}_\infty) = \omega$ by contradiction for each possible value of ω.

Consider $\omega = \sigma_\omega$ and assume $\mathbb{E}(\omega|\mathcal{H}_\infty) \neq \sigma_\omega$. In this case, the probability of informed buying is $F\left(\frac{\sigma_\omega + \tilde{\mu} - A_t^*}{\sigma^2}\right)\delta$ and $A_t^* < \sigma_\omega + \tilde{\mu}$. Therefore, informed traders would still trade with probability $\delta F(d)$ where $d > 0$, which we assumed is a positive probability. Hence, after a buy, market makers beliefs will be higher than $\mathbb{E}(\omega|\mathcal{H}_\infty)$. We arrived at a contradiction as $\mathbb{E}(\omega|\mathcal{H}_\infty)$ is constant by (13).

Consider the opposite case, $\omega = -\sigma_\omega$, and assume $\mathbb{E}(\omega|\mathcal{H}_\infty) \neq -\sigma_\omega$. In this case, the probability of informed selling is $F\left(\frac{B_t^* + \sigma_\omega - \tilde{\mu}}{\sigma^2}\right)\delta$ and $B_t^* > -\sigma_\omega + \tilde{\mu}$. Therefore, informed traders would still trade with probability $\delta F(d)$ where $d > 0$, which we assumed is a positive probability. Hence, after a sale, market makers beliefs will be lower than $\mathbb{E}(\omega|\mathcal{H}_\infty)$. We arrived at a contradiction as $\mathbb{E}(\omega|\mathcal{H}_\infty)$ is constant by (13).

□

Proof. Proposition 4

As noise traders trade equally by assumption, it is enough to show that informed traders trade more. Specifically, I show that:

$$F\left(\frac{\sigma_\omega + \mu - A_{1t_R}^*}{\sigma_\varepsilon}\right) > F\left(\frac{\sigma_\omega - A_{0t_R}^*}{\sigma_\varepsilon + \sigma_\mu}\right) \tag{14}$$

which is the probability that an investor trades given she is informed and $\omega = \sigma_\omega$. Note that, focusing in the ask side of the book, both quantities would be equal if:

$$A_{1t_R} = \mu + \sigma_\omega + (A_{0t_R}^* - \sigma_\omega)\frac{\sigma_\varepsilon}{\sigma_\varepsilon + \sigma_\mu} \equiv \bar{A}.$$

Since $g_A(A_{0,t}^*) = 0$ by definition; furthermore $P(\omega = \sigma_\omega | d = 1, \mathcal{H}_t)$ is the same in both scenarios as the probability of informed trading is the same,

$$g_A(\overline{A}) = \overline{A} - A_{0,t_R}^* \Rightarrow g(\overline{A}) = \left(1 - \frac{\sigma_\varepsilon}{\sigma_\varepsilon + \sigma_\mu}\right)\left(\sigma_\omega - A_{0t_R}^*\right) > 0.$$

As $g_A(\cdot)$ is increasing and $g_A(A_{1t_R}^*) = 0$ then, $\bar{A} > A_{1t_R}^*$. Therefore, (14) is satisfied. The case of the bid side follows a similar proof.

The limiting result is trivial using Lemma 2 □

Proof. Proposition 3

To show the effect on spreads, the following results are useful. $P_1(\omega = \sigma_\omega | \mathcal{H}_{t_R})$ equals

$P_0(\omega = \sigma_\omega|\mathcal{H}_{t_R})$ by construction, as models are identical until t_R, and $P_0(d = -1|\omega = \sigma_\omega, \mathcal{H}_{t_R}) = \frac{1}{2}(1-\delta) = P_1(d = -1|\omega = \sigma_\omega, \mathcal{H}_{t_R})$, that is, regardless if there is public news or not, only uniformed sell when the value of the private component of the asset is high. From the zero-profit condition, we know that:

$$A^*_{1t_R} - A^*_{0t_R} = \mu + 2\sigma_\omega \left[P_1(\omega = \sigma_\omega|d_{t_R} = 1, \mathcal{H}_{t_R}) - P_0(\omega = \sigma_\omega|d_{t_R} = 1, \mathcal{H}_{t_R})\right]$$

which we can rewrite using Bayes' rule as:

$$A^*_{1t_R} - A^*_{0t_R} = \mu + \left[\frac{P_1\left(d_{t_R} = 1|\omega = \sigma_\omega \mathcal{H}_{t_R}\right)}{P_1\left(d_{t_R} = 1|\mathcal{H}_{t_R}\right)} + \frac{P_0\left(d_{t_R} = 1|\omega = \sigma_\omega \mathcal{H}_{t_R}\right)}{P_0\left(d_{t_R} = 1|\mathcal{H}_{t_R}\right)}\right] P(\omega = \sigma_\omega|\mathcal{H}_{t_R}) 2\sigma_\omega$$

Using the law of total probability and the results stated at the beginning, we get

$$A^*_{1t_R} - A^*_{0t_R} = \mu + \frac{P(\omega = \sigma_\omega|\mathcal{H}_{t_R})^2\,(1-\delta)\,\delta\left(F\left(\frac{\sigma_\omega + \mu - A^*_{1t}}{\sigma_\varepsilon}\right) - F\left(\frac{\sigma_\omega - A^*_{0t}}{\sigma_\varepsilon + \sigma_\mu}\right)\right)}{P_1\left(d_{t_R} = 1|\mathcal{H}_{t_R}\right) P_0\left(d_{t_R} = 1|\mathcal{H}_{t_R}\right)}\sigma_\omega$$

therefore, given (14) , $A^*_{1t_R} - \mu > A^*_{0t_R}$. The same proof can be easily extended to bid prices to obtain that $B^*_{1t_R} - \mu < B^*_{0t_R}$. Thus, $A^*_{1t_R} - B^*_{1t_R} > A^*_{0t_R} - B^*_{0t_R}$.

Note that the independence of μ and the limiting case follow straightforward from the proof of Proposition 4, and Lemma 2.

□

References

Antweiler, W., Frank, M. Z., 2004. Is all that talk just noise the information content of internet stock message boards. The Journal of Finance 59, 1259–1294.

Bakshi, G., Kapadia, N., Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. The Review of Financial Studies 16, 101–143.

Ball, R., Brown, P., 1968. An empirical evaluation of accounting income numbers. Journal of Accounting Research pp. 159–178.

Barber, B. M., Loeffler, D., 1993. The dartboard column: Second-hand information and price pressure. Journal of Financial and Quantitative Analysis 28, 273–284.

Beaver, W. H., 1968. The information content of annual earnings announcements. Journal of Accounting Research pp. 67–92.

Bernard, V. L., Thomas, J. K., 1989. Post-earnings-announcement drift: delayed price response or risk premium? Journal of Accounting Research pp. 1–36.

Bernard, V. L., Thomas, J. K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting and Economics 13, 305–340.

Berry, T. D., Howe, K. M., 1994. Public information arrival. The Journal of Finance 49, 1331–1346.

Bollerslev, T., Li, J., Xue, Y., 2018. Volume, volatility and public news announcements. Review of Economics Studies .

Brown, S., Hillegeist, S. A., Lo, K., 2009. The effect of earnings surprises on information asymmetry. Journal of Accounting and Economics 47, 208–225.

Chae, J., 2005. Trading volume, information asymmetry, and timing information. The

Journal of Finance 60, 413–442.

Chan, W. S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. Journal of Financial Economics 70, 223–260.

Cohen, L., Malloy, C., Pomorski, L., 2012. Decoding inside information. The Journal of Finance 67, 1009–1043.

Demeterfi, K., Derman, E., Kamal, M., Zou, J., 1999. More than you ever wanted to know about volatility swaps. Goldman Sachs quantitative strategies research notes 41, 1–56.

Dubinsky, A., Johannes, M., Kaeck, A., Seeger, N. J., 2019. Option Pricing of Earnings Announcement Risks. The Review of Financial Studies 32, 646–687.

Easley, D., Kiefer, N. M., O'Hara, M., 1997. One day in the life of a very common stock. Review of Financial Studies 10, 805–835.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19, 69–90.

Ederington, L. H., Lee, J. H., 1993. How markets process information: News releases and volatility. The Journal of Finance 48, 1161–1191.

Elder, J., Miao, H., Ramchander, S., 2012. Impact of macroeconomic news on metal futures. Journal of Banking & Finance 36, 51–65.

Fleming, M. J., Remolona, E. M., 1999. Price formation and liquidity in the us treasury market: The response to public information. The Journal of Finance 54, 1901–1915.

Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. Accounting Review pp. 574–603.

Glosten, L. R., Milgrom, P. R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 14, 71–100.

Green, T. C., 2004. Economic news and the impact of trading on bond prices. The Journal of Finance 59, 1201–1233.

Hendershott, T., Menkveld, A. J., 2014. Price pressures. Journal of Financial Economics 114, 405–423.

Hess, D., Huang, H., Niessen, A., 2008. How do commodity futures respond to macroeconomic news? Financial Markets and Portfolio Management 22, 127–146.

Ho, T., Stoll, H. R., 1981. Optimal dealer pricing under transactions and return uncertainty. Journal of Financial Economics 9, 47–73.

Holden, C. W., Jacobsen, S., 2014. Liquidity measurement problems in fast, competitive markets: expensive and cheap solutions. The Journal of Finance 69, 1747–1785.

Holden, C. W., Subrahmanyam, A., 1994. Risk aversion, imperfect competition, and long-lived information. Economics Letters 44, 181–190.

Kandel, E., Pearson, N. D., 1995. Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103, 831–872.

Kim, O., Verrecchia, R. E., 1991. Market reaction to anticipated announcements. Journal of Financial Economics 30, 273–309.

Kim, O., Verrecchia, R. E., 1994. Market liquidity and volume around earnings announcements. Journal of Accounting and Economics 17, 41–67.

Koijen, R. S., 2014. The cross-section of managerial ability, incentives, and risk preferences. The Journal of Finance 69, 1051–1098.

Krinsky, I., Lee, J., 1996. Earnings announcements and the components of the bid-ask spread. The Journal of Finance 51, 1523–1535.

Kyle, A. P., 1985. Continuous Auctions and Insider Trading. Econometrica 53, 1315–1335.

Lee, C. M., Mucklow, B., Ready, M. J., 1993. Spreads, depths, and the impact of earnings information: An intraday analysis. Review of Financial Studies 6, 345–374.

Liu, P., Smith, S. D., Syed, A. A., 1990. Stock price reactions to the wall street journal's securities recommendations. Journal of Financial and Quantitative Analysis 25, 399–410.

Madhavan, A., Smidt, S., 1991. A bayesian model of intraday specialist pricing. Journal of Financial Economics 30, 99–134.

O'Hara, M., 1995. Market microstructure theory, vol. 108. Blackwell Cambridge, MA.

Pasquariello, P., Vega, C., 2007. Informed and strategic order flow in the bond markets. Review of Financial Studies 20, 1975–2019.

Ranaldo, A., 2005. Intraday market dynamics around public information arrivals. In: *EFMA 2002 London Meeting, Forthcoming*.

Riordan, R., Storkenmaier, A., Wagener, M., Zhang, S. S., 2013. Public information arrival: Price discovery and liquidity in electronic limit order markets. Journal of Banking & Finance 37, 1148–1159.

Sastry, R., Thompson, R., 2018. Strategic trading with risk aversion and information flow. Journal of Financial Markets .

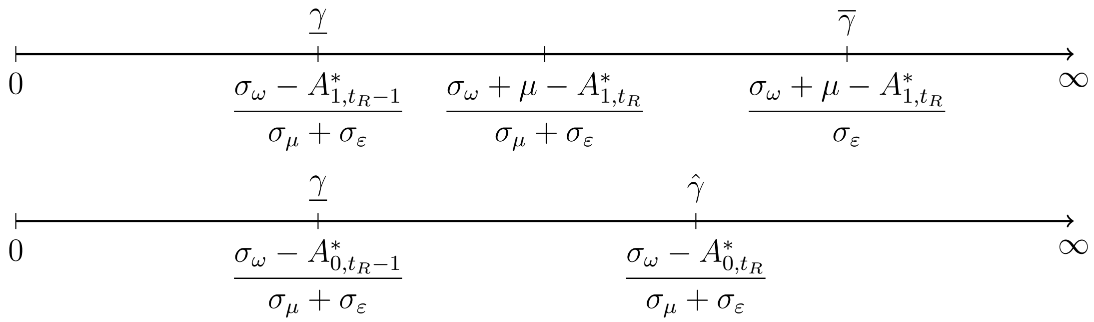
Savor, P., Wilson, M., 2016. Earnings announcements and systematic risk. The Journal of Finance 71, 83–138.

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

Vega, C., 2006. Stock price reaction to public and private information. Journal of Financial Economics 82, 103–133.

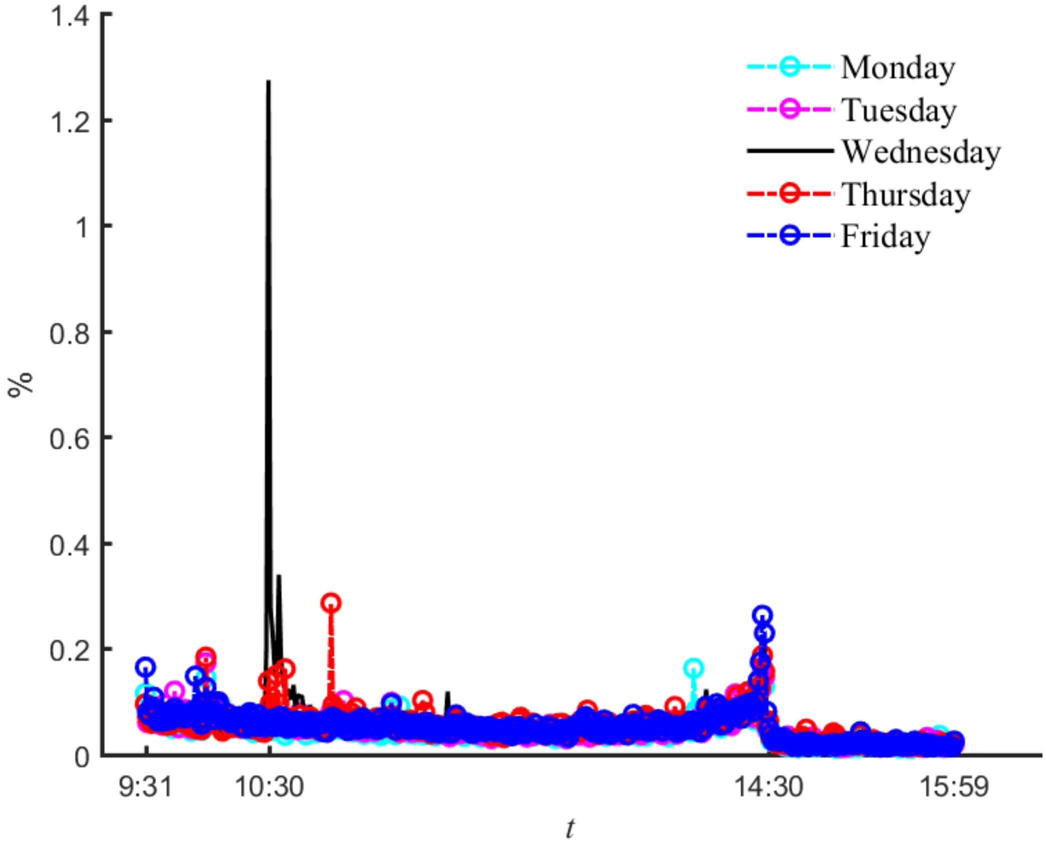
Figures

Figure 1: Illustration of the change in the composition of traders.



This figure sketches the main mechanism in the model if $\omega = \sigma_\omega$ and $d_{t_R-1} = -1$. Both lines represent the support of the risk-aversion parameter. The upper line depicts the relevant thresholds under the existence of a public signal whereas the bottom line consider the case without one. Investors whose risk aversion is below $\underline{\gamma}$ participate in the market in the period before the news are released. In the following period those with risk aversion below $\hat{\gamma}$ trade if there is no public announcement while every investor with risk aversion below $\overline{\gamma}$ participates in the case that public information is revealed.

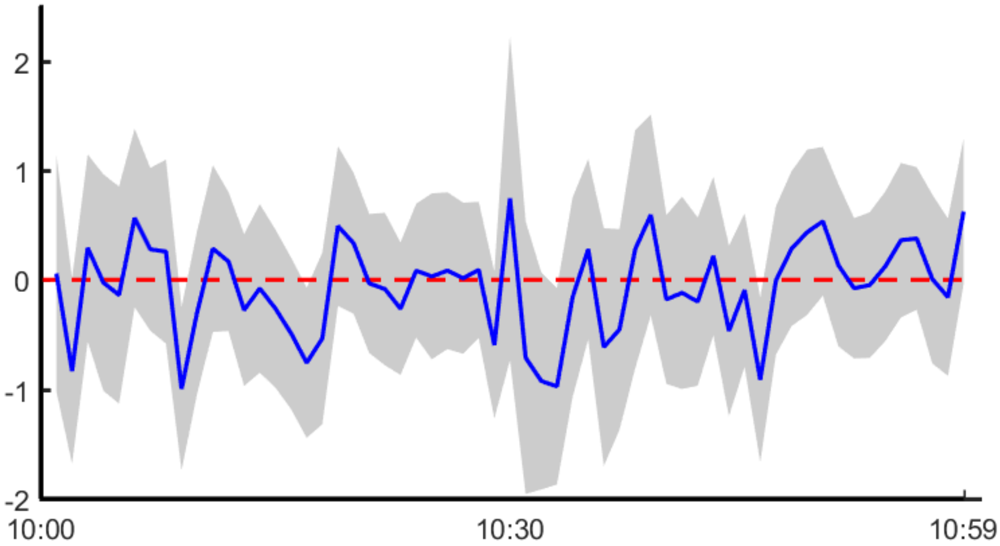
Figure 2: Intraday variance decomposition



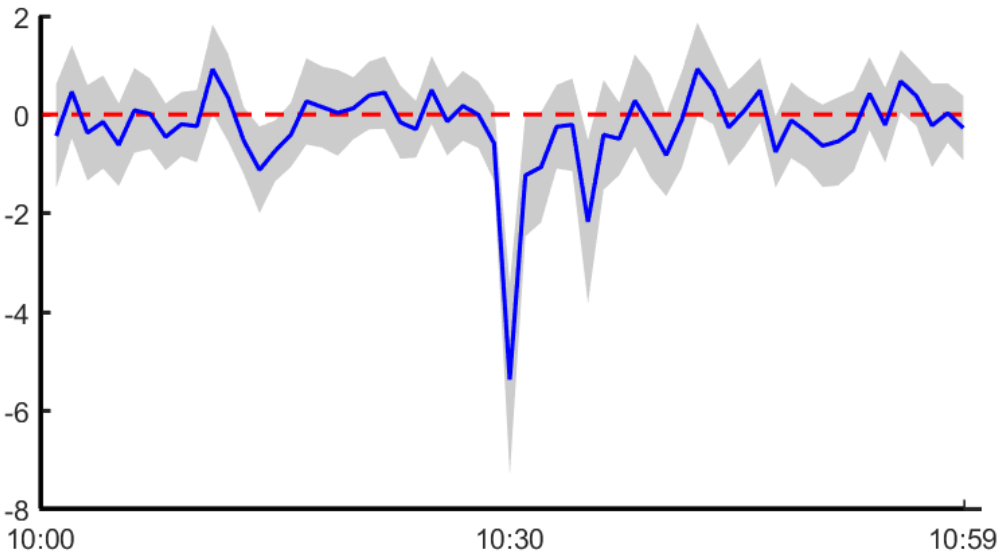
This figure presents the sample realized variance of the nearest-maturity future by minute normalized to sum to 100% every week.

Figure 3: Estimated effect of the announcement on returns.

(a) $Wed \cdot Oil$ (γ_1)



(b) $Wed \cdot Oil \cdot News$ (γ_2)

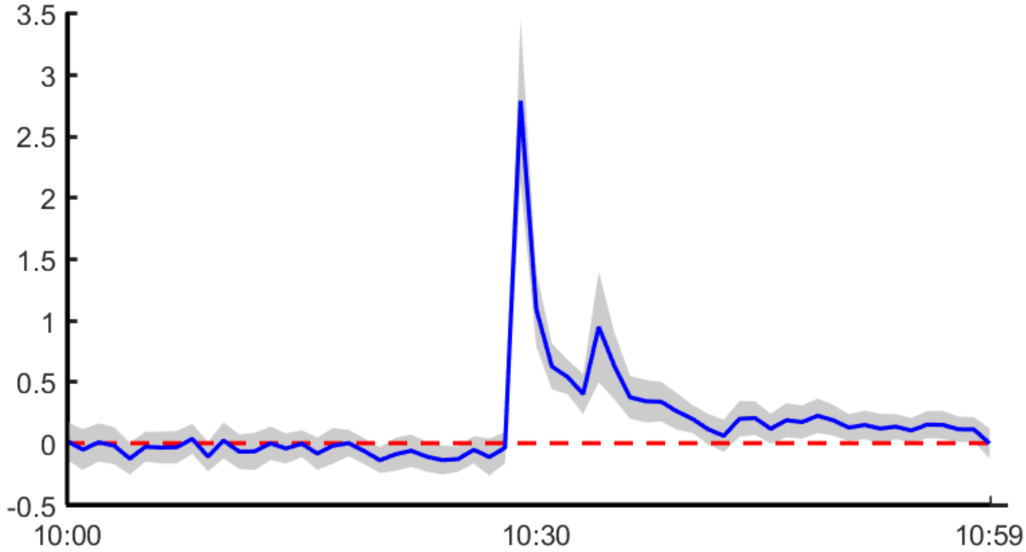


	10:00-10:28		**10:29**		**10:30**		**10:31-10:59**	
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
Mean	-0.07	-0.07	-0.60	-0.58	0.74	-5.38‡	-0.06	-0.24
Rejections	0.07	0.11	0.00	0.00	0.00	1.00	0.07	0.10

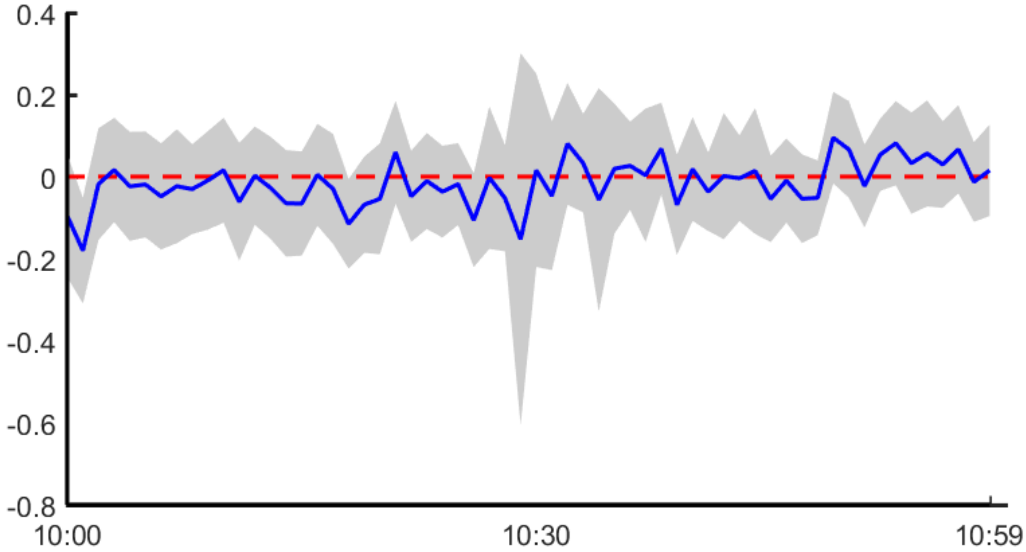
Estimates (blue line) and their 95 % confidence interval (grey area) of the regression equation (3) using midpoint returns (bp) as a dependent variable. The table at the bottom summarizes the mean estimates and the proportion of minutes in which we can reject that the parameter equals zero at the 5% significance level. ‡ indicates that the null of all the estimates being equal to zero is rejected at the 5% significance level under the assumption of independence of coefficients across minutes. The sample includes 50 random firms from January 2007 to June 2013.

Figure 4: Estimated effect of the announcement on bid-ask spreads.

(a) $Wed \cdot Oil$ (γ_1)



(b) $Wed \cdot Oil \cdot News$ (γ_2)

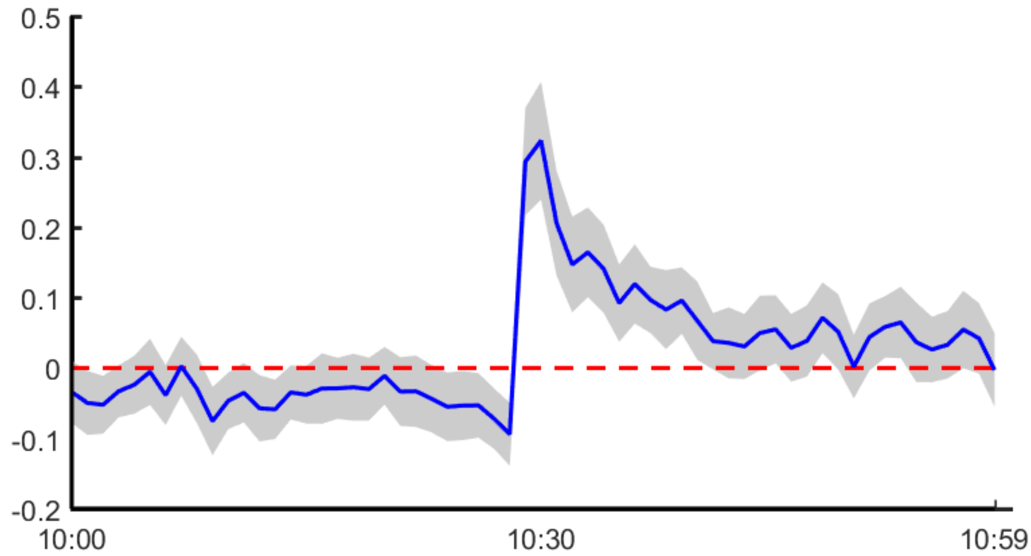


	10:00-10:28		**10:29**		**10:30**		**10:31-10:59**	
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
Mean	-0.05	-0.04	$2.78^{\ddagger}$	-0.15	$1.09^{\ddagger}$	0.02	$0.25^{\ddagger}$	0.01
Rejections	0.10	0.07	1.00	0.00	1.00	0.00	0.83	0.00

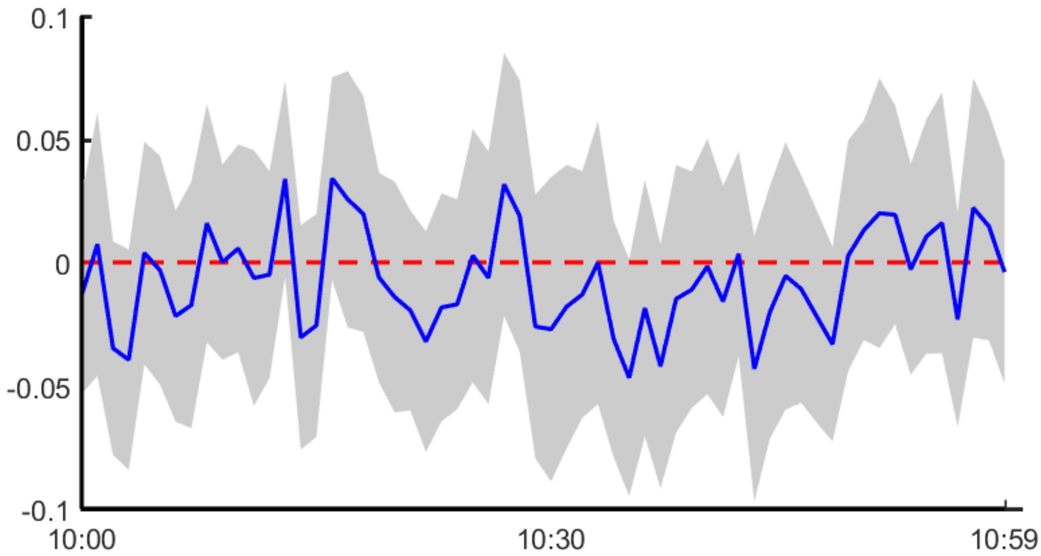
Estimates (blue line) and their 95 % confidence interval (grey area) of the regression equation (3) using proportional effective bid-ask spreads (pp) as a dependent variable. The table at the bottom summarizes the mean estimates and the proportion of minutes in which we can reject that the parameter equals zero at the 5% significance level. ‡ indicates that the null of all the estimates being equal to zero is rejected at the 5% significance level under the assumption of independence of coefficients across minutes. The sample includes 50 random firms from January 2007 to June 2013.

Figure 5: Estimated effect of the announcement on volume.

(a) $Wed \cdot Oil \ \ (\gamma_1)$



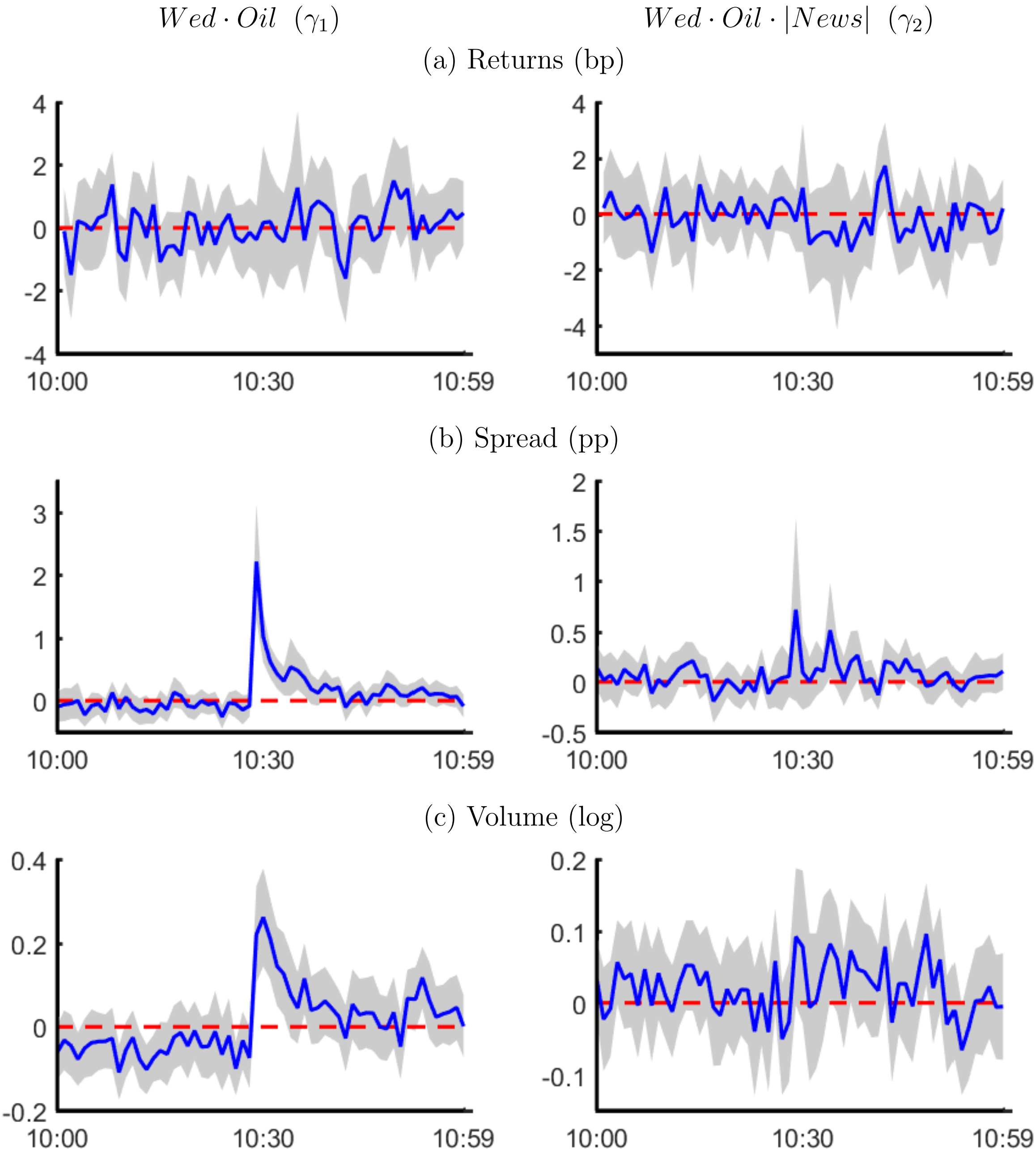
(b) $Wed \cdot Oil \cdot News \ \ (\gamma_2)$



	10:00-10:28		**10:29**		**10:30**		**10:31-10:59**	
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
Mean	-0.04‡	-0.00	0.29‡	-0.03	0.32‡	-0.03	0.07‡	-0.01
Rejections	0.38	0.00	1.00	0.00	1.00	0.00	0.48	0.00

Estimates (blue line) and their 95 % confidence interval (grey area) of the regression equation (3) using number of transactions (logs) as a dependent variable. The table at the bottom summarizes the mean estimates and the proportion of minutes in which we can reject that the parameter equals zero at the 5% significance level. ‡ indicates that the null of all the estimates being equal to zero is rejected at the 5% significance level under the assumption of independence of coefficients across minutes. The sample includes 50 random firms from January 2007 to June 2013.

Figure 6: Effect of the announcement conditional on the absolute surprise.



	Returns		**Spread**		**Volume**	
10:30	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
Estimate	0.17	0.94	$1.02^{\ddagger}$	0.09	$0.26^{\ddagger}$	0.08
Std. Error	1.24	1.17	0.21	0.19	0.06	0.05

This figure plots the estimates (blue line) and their 95 % confidence interval (grey area) of the model described in equation (4). Each row considers a different dependent variable. The left-hand (right-hand) side plots correspond to γ_1 (γ_2). The table at the bottom summarizes the estimates and standard errors at 10:30. ‡ indicates that the estimates are different from zero at the 5% significance level. The sample includes 50 random firms from January 2007 to June 2013.

Tables

Table 1: Summary of Alternative Mechanisms

	Effect if **News** = **0**		Effect of |**News**|	
	Volume	Market quality	Volume	Market quality
Data	$\color{green}\uparrow$	$\color{green}\downarrow$	$\color{green}\emptyset$	$\color{green}\emptyset$
Endogeneous Participation *This Paper*	$\color{green}\uparrow$	$\color{green}\downarrow$	$\color{green}\emptyset$	$\color{green}\emptyset$
Asymmetric Information Resolution Tetlock (2010)	$\color{green}\uparrow$	$\color{red}\uparrow$	$\color{red}\uparrow$	$\color{green}\emptyset$
Disagreement Kandel and Pearson (1995) Pasquariello and Vega (2007)	$\color{green}\uparrow$	$\color{red}\uparrow$	$\color{green}\uparrow$	$\color{red}\uparrow$
Asy. Info. Processing Technologies Kim and Verrecchia (1991, 1994)	$\color{green}\uparrow$	$\color{green}\downarrow$	$\color{red}\uparrow$	$\color{red}\downarrow$

This table summarizes the sign prediction of previous models according to the realization of the signal. The first two columns (**News** = **0**) describe the reaction to the announcement when its value effect is zero. The last two columns provide the predicted effect of the absolute value of the actual realization on the reaction to the announcement. The data line corresponds to the empirical results of this paper. Models differ in the definition of market quality, I consider an indication of high market quality: lower spreads, higher depth or lower price impact. If alternative models provide ambiguous predictions, I indicate the prediction that coincides with the empirical results. Green (red) indicates that the prediction of the model (dis)agrees with the data.

Table 2: Effects conditional on the public signal strength.

	Return	Spread	Volume
Panel A: Unexpected inventory change			
$Oil \cdot Wed$	0.70	1.51‡	0.43‡
	(1.04)	(0.18)	(0.05)
$Oil \cdot Wed \cdot News$	-6.34‡	0.03	-0.03
	(1.34)	(0.16)	(0.04)
$Oil \cdot Wed \cdot \widehat{\sigma_\mu}$	-0.04	0.52‡	0.13‡
	(0.67)	(0.09)	(0.03)
$Oil \cdot Wed \cdot News \cdot \widehat{\sigma_\mu}$	-1.20	0.01	-0.01
	(0.79)	(0.12)	(0.04)
Panel B: Absolute unexpected inventory change			
$Oil \cdot Wed$	0.91	1.46‡	0.35‡
	(1.84)	(0.23)	(0.07)
$Oil \cdot Wed \cdot \lvert News \rvert$	0.04	0.05	0.10
	(2.03)	(0.22)	(0.06)
$Oil \cdot Wed \cdot \widehat{\sigma_\mu}$	0.68	0.63‡	0.11‡
	(1.08)	(0.15)	(0.05)
$Oil \cdot Wed \cdot \lvert News \rvert \cdot \widehat{\sigma_\mu}$	-0.81	-0.15	0.03
	(1.31)	(0.15)	(0.05)

Panel A presents the estimation results of Equation (5) using returns (bp), proportional bid-ask spreads (pp) and the logarithm of the number of transactions at 10:30 a.m. Panel B considers the estimation of the same equation substituting $News$ by its absolute value. $\widehat{\sigma_\mu}$ is a measure of the signal relevance with standard deviation equal to one. ‡ indicates that the coefficients are significant at the 95% significance level. The sample includes 50 random firms from January 2007 to June 2013.

Table 3: Implied Volatility and Informed Trading.

Panel A: Implied Volatility

	OptionMetrics	Demeterfi et al. (1999)	Bakshi et al. (2003)
$AW \cdot Oil$	-0.38‡	-0.47‡	-0.55‡
	(0.18)	(0.21)	(0.18)
$AW \cdot Oil \cdot News$	-0.01	0.26	0.21
	(0.18)	(0.24)	(0.20)

Panel B: Insider Trading

	All Insiders		Opportunistic Insiders	
	Volume	Imbalance	Volume	Imbalance
$Wed \cdot Oil$	0.16‡	-0.02	0.16‡	-0.01
	(0.03)	(0.01)	(0.04)	(0.02)
$Wed \cdot Oil \cdot News$	0.06	-0.03	0.03	-0.03
	(0.04)	(0.02)	(0.05)	(0.02)

Panel A presents the estimation results of Equation (6) using three different measures of implied volatility (pp). Panel B presents the estimation results of equation (7) using as dependent variable the log of the number of shares transacted and the difference between shares bought and sold by insiders normalized by the sum of the two -labeled imbalance. The left columns include all insiders while the right columns include just oportunistic insiders as defined by Cohen, Malloy, and Pomorski (2012). ‡ indicates that the coefficients are significant at the 95% significance level. The sample includes 50 random firms from January 2007 to June 2013.