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Pedro A. C. Saffi[1]

[1] Professor of Financial Management, IESE

IESE Business School – University of Navarra
Av. Pearson, 21 – 08034 Barcelona, Spain. Phone: (+34) 93 253 42 00 Fax: (+34) 93 253 43 43
Camino del Cerro del Águila, 3 (Ctra. de Castilla, km 5,180) – 28023 Madrid, Spain. Phone: (+34) 91 357 08 09 Fax: (+34) 91 357 29 13

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Differences of Opinion, Information and the Timing of Trades

Pedro A. C. Saffi *†

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Abstract

This paper focuses on the impact that dispersion of opinions and asymmetric information have on turnover near releases of public information, using the probability of informed-based trading (PIN) to proxy for information asymmetry and analysts' forecast dispersion for differences of opinion. For earnings announcements of US firms, I find that a one standard deviation increase in dispersion accelerates trading, reducing the difference between turnover around and turnover before announcements by 8.50%. A similar increase in PIN delays trading, raising the difference by 8.29%. These results help to explain why a large number of events have high turnover before earnings announcements relative to turnover after their release. Furthermore, the information contained in the time-series difference between trading around and before announcements helps to disentangle the impact of information asymmetry from that of proxies for differences of opinion.

I also present a theoretical model in which agents who receive private information of heterogeneous quality, trade a stock before and after observing a public signal. This public signal is interpreted differently across agents, leading to differences of opinion. I obtain closed-form solutions for expected aggregate volume and its derivatives with respect to these variables, showing that extending static models of asymmetric information is not enough to match the empirical findings.

JEL classification: G14, G10, G12.

Keywords: Trading volume, differences of opinion, information asymmetry.

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† IESE Business School. Email: psaffi@iese.edu. Web: http://webprofesores.iese.edu/PSaffi

1 Introduction

Research on what makes investors trade can help to identify which sources of heterogeneity are important for pricing assets and determining equilibrium levels of trading volume. Studying stock turnover can also reveal information about the type of investors trading a particular security. Chae (2005) shows that stock turnover decreases on days right before earnings announcements and increases afterwards. However, almost 35% of stocks on CRSP exhibit greater average turnover before earnings announcements than during non-event days. In many cases, this increased turnover before announcements is even higher than turnover around announcements. At first, this might seem puzzling, since risk-averse, uninformed investors would prefer to trade after the release of information, when they face a smaller probability of losing money to investors with superior information. In this paper, I show that differences of opinion about earnings announcements help to explain these observed differences.

Trading is generated whenever investors have different valuations about asset value. Heterogeneous valuations can be generated through many different channels, such as giving agents differential amounts of information about the asset, heterogeneous prior beliefs or differential interpretation of information. Most purely-rational equilibrium models imply that trading volume is negatively related to information asymmetry [Kim and Verrecchia (1991, 1994); Wang (1994); He and Wang (1995); Verrecchia (2001)]. These models show that while price fluctuations reflect changes in average beliefs, trading volume is determined by differential revisions of individual beliefs, caused by heterogeneous priors or access to private information. Even if the average belief does not change upon arrival of new information, implying that prices remain the same, trading can still occur whenever the level of investor disagreement is affected.

An alternative channel to explain trading behavior is differential interpretation of information, by which agents disagree about how to interpret the information disclosed by public signals. Although everyone observes the same information, its outcome is interpreted by some traders as good news, while others interpret it as being bad news. In this setting, public information is still common knowledge to investors, but each one has a different likelihood function to evaluate how public signals affect asset valuation, generated by the disagreement on the meaning of public information.[1]

[1]This is a quote from the article "Swimming against the Tide", *Business Week*, Sep. 23rd, 2005: "It's nearly impossible to get people to agree completely on certain topics. Who was the greatest U.S. President? Is the designated

This assumption leads to differential updating of beliefs and to a higher trading volume, even when all agents start out with the same prior assumptions about the asset. Imagine, for example, a corporate event that makes half the investors more optimistic and the other half equally more pessimistic about a stock. Although aggregate beliefs stay the same, the more pessimistic agents would happily sell their holdings to the more optimistic ones, generating trading volume without any price change. Although this assumption is not common in rational-expectations models, it has been widely used as an alternative way to generate trading and explain the empirical fact that in many situations stock turnover is very high even when prices remain unchanged [Harris and Raviv (1993); Kandel and Pearson (1995); Banerjee and Kremer (2005)].

This paper expands the literature on trading volume in two dimensions. First, I combine features from Kim and Verrecchia (1991) and Kandel and Pearson (1995) to solve a model that incorporates both information asymmetry and differential interpretation of information, in a non-myopic economy where no single agent has a strictly better information set than others. Agents observe private signals before the release of public information, but the precision of these signals varies across agents. When the public signal is released, though all agents observe the same information, there is differential interpretation about its meaning. I examine how these two features affect the difference in trading levels before and after releases of public information, and how the timing of these trades can be used to reveal characteristics about the information environment of a stock.

I derive analytical formulae for expected trading volume and show that higher dispersion increases expected aggregate turnover both before and around announcements. An increase in information asymmetry decreases trading by uninformed investors before announcements, but the aggregate effect depends on how much extra trading is soaked up by relatively better informed investors. After announcements, higher asymmetry unambiguously decrease aggregate trading volume.

However, simply extending three-period volume models to incorporate differential interpretations of public signals [as in Kandel and Pearson (1995)] cannot explain the time-series differences in turnover before and turnover around earnings announcements found in the data. The model predicts that higher dispersion delays trading, as the fall in uncertainty following the release of public information makes investors even more willing to trade on their differential beliefs. This result is

hitter rule good for baseball? Rare, medium, or well-done? Is Stock X a buy or a sell? Of course, it's that last question that concerns us. Equity research outfits' opinions on particular issues can vary widely. That's because analysts may use different valuation models, industry forecasts, macroeconomic assumptions, etc., in arriving at their recommendations."

strongly rejected empirically and I find the opposite sign in the data, even though the model is able to successfully capture the patterns observed for trading levels at the time of earnings announcements.

Empirically, information asymmetry is captured by the probability of information-based trading (PIN), developed by Easley, Kiefer, and O'Hara (1996) and computed from high-frequency trading data to provide an estimate of the amount in private information-based trading for a particular stock. Differences of opinion are captured by analysts' forecast dispersion, using several instruments to filter the impact of fundamental uncertainty and information asymmetry on dispersion.

Using earnings announcements by US firms from 1984 to 2002, I find that a one standard deviation increase in dispersion accelerates trading, reducing the difference between turnover around and turnover before announcements by 8.50%. A similar increase in information asymmetry delays trading, raising the difference by 8.29%. These results show that combining information asymmetry and dispersion of opinion improves explanation of turnover and the time-series difference between trading before and around an announcement, being robust to the periodicity of announcements (quarterly or annual), different sample periods and alternative lengths of the "around"-announcements window.

The combination of changes in dispersion and information asymmetry help to explain why some stocks actually have higher turnover before announcements, a characteristic exhibited by about one third of events in my sample. Any model that attempts to explain trading volume must be able to explain this cross-sectional heterogeneity in turnover differences, on top of any effects related to levels of turnover. This requires a fully dynamic model that allows trading at different periods before and after releases of public signals that includes differential interpretation of public signals. My results also provide new evidence that analyst dispersion is more closely related to differences of opinion [Diether, Malloy, and Scherbina (2002)] than to fundamental uncertainty [Johnson (2004)].

The rest of the paper is divided as follows. Section 2 describes the related literature, while section 3 contains the model and analytical formulas derived for expected trading volume. Section 4 describes the hypotheses. In section 5, I discuss the empirical results. Section 6 summarizes my findings and the appendix collects all proofs.

2 Literature Review

The mechanism behind most models attempting to explain trading is some type of heterogeneity that makes agents update their beliefs about asset value in different ways. Explored sources have been ones such as agents who observe signals of different precisions [Grundy and McNichols (1989); Kim and Verrecchia (1991, 1994); He and Wang (1995)], have access to different investment opportunities [Wang (1994)], face heterogeneous endowment shocks [Schneider (2005)] or are overconfident about the information they receive [Odean (1998)].

My paper is related to Kim and Verrecchia (1991) in the sense that traders also receive private signals of different quality. After a (noisy) public announcement about firm value, they show how trading volume is proportional to the absolute price change times a measure of the level of pre-disclosure information asymmetry among investors. Trading arises due to differential belief revisions caused by asymmetric *private* information among investors, with some agents having strictly better information sets than others. Trade cannot occur without being accompanied by price changes, a counterfactual feature of their model.

I address this concern by assuming differential interpretation of public information, in which each agent has a unique way of processing public information [Harrison and Kreps (1978); Harris and Raviv (1993)]. I follow the approach of Kandel and Pearson (1995) and Banerjee and Kremer (2005) by giving each agent a different likelihood function about an informative public signal. Although everyone observes the same signal, each agent interprets it uniquely, leading to differential updating of beliefs even when all agents start out with the same priors. In contrast to these papers, I not only explicitly model private signals, but also consider agents who incorporate the information contained in prices to update their beliefs.

The impact of information asymmetry in my model is similar to Wang (1994). In his paper, some agents not only have superior information but also have access to better investment opportunities. They can be thought of as sophisticated institutions like banks, pension funds or fund managers who would have better access to information and a wider variety of investment opportunities not commonly available to individual investors or those in less-developed markets. Those receiving superior information, the informed ones, dynamically trade for informational and non-informational reasons. Uninformed investors only accept to trade with informed ones because they know that not all trades will be due to information shocks directly affecting the asset value. Hence, as asymmetric information increases, uninformed investors are less capable of identifying the motivation behind the informed investors' trades and their trading volume decreases as a consequence. A more realistic assumption is to prevent that the information sets of certain agents are strictly superior to other, which is done by He and Wang (1995) in a discrete-time economy with a terminal date.[2] Although I use a simpler model with only two trading dates compared to their more realistic dynamic version, in both models agents observe private signals of heterogenous quality, but no one is perfectly informed about the liquidation value of the asset. Investors differ by their prior expectations about *public* information and by observing private information unknown to others. The finite-horizon setting implies that trades depend not only on cash-flow uncertainty but also on the number of trading opportunities still remaining. As time elapses, more private information is revealed through prices, inducing agents to speculate more. On the flip-side, as the terminal date approaches there are fewer trading opportunities, making it harder to unwind positions and leading to less aggressive behavior by investors. In equilibrium, the opposing effects of these two forces determine portfolio holdings and volume patterns.

On the empirical side, many papers have looked at trading volume using corporate earnings announcements. For example, Atiase and Bamber (1994) show evidence that trading volume reactions around announcements are an increasing function of the level of pre-disclosure informational asymmetry using analyst forecast dispersion as a proxy for information asymmetry. Unlike their paper, I use dispersion as a proxy for differences of opinion [Diether, Malloy, and Scherbina (2002)], examining its impact on turnover measures after controlling for the idiosyncratic risk and information asymmetry components.

Also related is Bamber, Barron, and Stober (1997), who show that different aspects of disagreement affects trading around announcements. On top of dispersion of prior beliefs, changes in aggregate dispersion following the announcement and changes in the relative forecasts of individual analysts are also important, but they don't control for the level of information asymmetry surrounding an announcement.

Closest to my work is Chae (2005), who presents evidence that trading volume reactions decrease with information asymmetry before scheduled announcements and increase afterwards. I

[2] Relaxing this assumption in a infinite-horizon setting requires solving a filtering-problem with an infinite number of state variables. An agent would have to forecast the forecasts of others. His own forecast of the forecast would then also have to be forecasted by other agents, leading to the "infinite regress" problem [Townsend (1983)].

contribute by showing that differences of opinion are important to determine trading levels and, more importantly, that the time-series difference between trading around and before announcements helps to disentangle the impact of information asymmetry from those of proxies of differences of opinion.

3 Model

The model is based on a generalization of Kim and Verrecchia (1991) to allow for differences of opinion as in Kandel and Pearson (1995). Agents receive private information of heterogeneous quality (generating asymmetric information among them) and have different opinions about public information (leading to differential likelihood functions). The setting is fully-rational in the sense that prices are also used to infer the true liquidation value of a risky asset.

These two sources of information generate a trade-off between a larger willingness to trade as differences of opinion increase among investors and an increased fear of being exploited by investors who observe more precise private signals. In equilibrium, mean-preserving spreads in the distribution of opinions about the public signal will affect trading volume while leaving prices unchanged.

The economy has a continuum of traders indexed by $i \in [0, 1]$, each having CARA utility function with risk aversion coefficient $\frac{1}{\lambda}$. They are allowed to trade two assets at two trading dates ($t = 1, 2$). The first asset is a riskless security that pays no interest, while the second is a risky stock in random supply liquidated at $t = 3$. The stock's terminal value is given by a random payoff X, which is normally distributed with mean $\bar{X}$ and precision (inverse of variance) h_X. The stock supply S is normally distributed with zero mean and precision h_S, preventing agents from fully learning the liquidation value after observing market prices.

All investors begin to trade having the same beliefs, which are equal to the unconditional mean $\bar{X}$ of the liquidation value. During the second round of trading, each agent observes a normally distributed private signal $Z_i = X + \varepsilon_i$, with ε_i having zero mean and precision t_i. The heterogeneous quality of private signals, generated by each unique precision t_i, creates asymmetric information across investors in this economy.

At the beginning of the last round of trading, the company releases a public signal with information about the liquidation value to the market. The release date of this signal is known to everyone, but its meaning is interpreted differently by each agent. This is the “agreeing-to-disagree” assumption [see Harrison and Kreps (1978); Kandel and Pearson (1995); Wang (1998) or Banerjee and Kremer (2005)] and is equivalent to observing a public signal $E = X + v$, with each investor believing that the normally distributed shock v has identical precision h_E but a different mean μ_i. The different opinions about the average value of the shock v makes each agent to have their own likelihood function when interpreting the outcome of the public signal, which in turn affects the updating of beliefs about the true value of the asset.

Finally, at $t = 3$, the firm is liquidated and investors consume all of their wealth. I assume that all random variables are independent from each other and their distributions are common knowledge to all agents in the economy. Figure 1 summarizes the events occurring at each trading date.

Agents condition their investment decisions on observed prices, fully using market information to update their beliefs about the asset. Because investors are not myopic and prices at $t = 2$ depend on the outcome of the public signal E, they take into account not only their expectations about the liquidation value X, but also their beliefs about E when choosing their portfolios at $t = 1$. Differential interpretation of public signals, measured by the parameter μ_i, creates an incentive to trade regardless of the asset's liquidation value. This incentive depends solely on disagreement about the meaning of the public signal. However, this willingness to speculate on differences of opinion is counterbalanced by the fact that some traders possess an informational advantage because they receive more precise private signals, making relatively uninformed investors less willing to trade. These two opposing forces, differences of opinion and information asymmetry, are crucial to determine levels of trading and its timing.

In noisy rational expectations equilibrium (NREE) models, investors make self-fulfilling conjectures about prices and one defines equilibrium as a set of allocations such that agents maximize their utilities, their conjectures hold and markets clear. Let these linear conjectures for P_1 and P_2 be given by:

$$\begin{aligned} P_1 &= \phi_1 + \alpha_1 \bar{X} + \beta_1 \int_0^1 Z_i di - \gamma_1 S \\ &= \phi_1 + \alpha_1 \bar{X} + \beta_1 \int_0^1 (X + \varepsilon_i)\, di - \gamma_1 S \\ &= \phi_1 + \alpha_1 \bar{X} + \beta_1 X - \gamma_1 S. \end{aligned} \tag{1}$$

and

$$P_2 = \phi_2 + \alpha_2 \bar{X} + \beta_2 X - \gamma_2 S + \theta_2 E. \quad (2)$$

In equilibrium, the noise contained in private signals is eliminated by the law of large numbers, simplifying the optimization problem because agents no longer need to forecast the forecasts of others when inferring information from prices. This is an issue with interesting implications of its own [see for example Townsend (1983); He and Wang (1995); Makarov and Rytchkov (2006)], but not crucial for my argument.

At $t = 1$, investors trade based on the information given by private signals Z_i and the market price P_1. At $t = 2$, they additionally use the public signal E and price P_2. The normalized signals q_1 and q_2 summarize the information contained in prices, defined as:

$$q_1 \equiv \frac{1}{\beta_1}\left[P_1 - \phi_1 - \alpha_1 \bar{X}\right] = X - \xi_1 S \quad (3)$$

$$q_2 \equiv \frac{1}{\beta_2}\left[P_2 - \phi_2 - \alpha_2 \bar{X} - \theta_2 E\right] = X - \xi_2 S \quad (4)$$

The precisions of the noise in variables Z_i, E, q_1, q_2 as linear functions of X are: $t_i, h_E, \frac{h_S}{(\xi_1)^2}$ and $\frac{h_S}{(\xi_2)^2}$. In this paper I assume that linear conjectures are such that $\xi_1 = \xi_2$, i.e., the elasticity of the signal with respect to the stock supply is the same over trading dates, making $q_1 = q_2 = q$.[3]

Since prices are perfectly determined by q_1 and q_2, the information sets of agent i at time t can be summarized by $\mathcal{F}_t^i$:

$$\mathcal{F}_1^i = \{Z_i, q_1\}.$$

$$\mathcal{F}_2^i = \{Z_i, E, q_1, q_2\}.$$

In standard fashion, I begin to solve the model by finding optimal demands at $t = 2$:

[3] I focus solely on partial information-revealing equilibrium. Please refer to section 2 of Grundy and McNichols (1989) for a more detailed discussion about the two types of equilibrium in a model without differences of opinion.

3.1 Trading at date 2

Investor i chooses optimal stock demand m_t^i at time t, by maximizing next period's wealth W_t^i given the information set $\mathcal{F}_t^i$. At $t = 2$, optimal stock demand is given by:

$$\begin{aligned} & \underset{\{m_2^i\}}{\text{Max}}\, E_i \left\{ -e^{-\frac{1}{\lambda}\left[W_2^i + m_2^i\left(\widetilde{X} - P_2\right)\right]} \mid \mathcal{F}_2^i \right\} \\ \Leftrightarrow \quad & \underset{\{m_2^i\}}{\text{Max}}\, \frac{m_2^i\left(E_i\left[\widetilde{X} \mid \mathcal{F}_2^i\right] - P_2\right)}{\lambda} - \frac{\left(m_2^i\right)^2}{2\lambda^2} Var\left[\widetilde{X} \mid \mathcal{F}_2^i\right]. \end{aligned} \tag{5}$$

In view of the CARA utility function and normality of random variables, Bayes' theorem ensure that traders update their beliefs about the liquidation value with:

$$E_i\left[\widetilde{X} \mid \mathcal{F}_2^i\right] = \frac{h_X \bar{X} + h_E\left(E - \mu_i\right) + t_i Z_i + \left(\frac{h_S}{\xi^2}\right) q}{h_X + t_i + h_E + \frac{h_S}{\xi^2}} \text{ and} \tag{6}$$

$$\frac{1}{Var\left[X / \mathcal{F}_2^i\right]} = K_{2i} = h_X + t_i + h_E + \frac{h_S}{\xi^2}. \tag{7}$$

At $t = 2$, differences in how investors estimate the liquidation value are due to private information heterogeneity and dispersion of opinions. Here, I assume there is no overconfidence by agents (i.e., h_E is constant), but they are allowed to disagree about the interpretation of public information. When a firm releases its earnings, the precision of beliefs rises by the same amount h_E for all agents, reducing total uncertainty. However, the effect of this announcement on individual valuations depends both on how optimistic an agent is (i.e., how negative μ_i is), and on the precision of the public signal relative to his prior's precision (i.e., how large h_E is relative to K_{1i}). The assumption of homogeneous precisions about the noise contained in these signals is important to eliminate any effects caused by overconfidence [Odean (1998)], which would affect asset returns and, consequentially, trading volume.

Furthermore, the release of public information reduces overall uncertainty and the gap between uninformed and informed traders' precision in estimating asset values. This can be seen from equation (7), which shows how a release of public information increases the precision about liquidation value's beliefs by h_E. This increase however, relative to *ex-ante* information, is relatively larger for uninformed investors.

The following theorem summarizes equilibrium at $t = 2$.

Theorem 1 *Equilibrium price and demands conditional on the public signal at $t = 2$ are characterized by stock price*

$$P_2 = \frac{1}{K_2}\left[h_X \bar{X} + \left(t + \lambda^2 t^2 h_S\right) X - \left(\frac{1}{\lambda} + \lambda t h_S\right) S + h_E \left(E - \mu\right)\right] \tag{8}$$

and demand

$$m_2^i = \lambda t_i \varepsilon_i + \lambda h_E \left(\mu - \mu_i\right) + \frac{\lambda \left(t_i - t\right)}{K_2}\left[h_X \left(X - \bar{X}\right) + h_E \left(v - \mu\right) + \lambda t h_S S\right] + \frac{K_{2i}}{K_2} S, \tag{9}$$

where $\mu = \int_0^1 \mu_i di$, $t = \int_0^1 t_i di$, $K_{2i} \equiv h_X + t_i + h_E + \lambda^2 t^2 h_S$ *and* $K_2 \equiv \int_0^1 K_{2i} di = h_X + \int_0^1 t_i di + h_E + \lambda^2 t^2 h_S$.

As expected, prices increase with X and decrease with aggregate supply S. The distribution of opinions in this economy affects prices through the term μ, which captures the average opinion about the public signal. When this parameter is greater than zero, investors on average infer a smaller realization of the liquidation value X from the earnings announcement, becoming relatively more pessimistic about it. Although prices are unaffected by differences of opinion when μ is zero, demands are still sensitive to individual beliefs and depend on how much they differ from the average. The more precise public signals are, the more weight is given to their outcome, leading to a higher impact from differences of opinion on investor holdings.

3.2 Trading at date 1

At $t = 1$, agents solve

$$\underset{\{m_1^i\}}{\text{Max}}\, E_i \left\{ -e^{\left(-\frac{1}{\lambda}\left[m_0^i\left(\widetilde{P_1} - P_0\right) + m_1^i\left(\widetilde{P_2} - P_1\right) + m_{i2}\left(\widetilde{X} - \widetilde{P_2}\right)\right]\right)} \mid \mathcal{F}_{i1} \right\}.$$

Using the law of iterated expectations we rewrite this expectation as:

$$E_i \left\{ E_i \left[-e^{\left(-\frac{1}{\lambda}\left[m_0^i\left(\widetilde{P_1} - P_0\right) + m_1^i\left(\widetilde{P_2} - P_1\right)\right] - \left(E_i\left[\widetilde{X} \mid \mathcal{F}_{i2}\right] - \widetilde{P_2}\right)\left(\widetilde{X} - \widetilde{P_2}\right) K_{2i}\right)} \mid \mathcal{F}_{i2} \right] \mid \mathcal{F}_{i1} \right\}.$$

In the Appendix, I show that this problem is equivalent to:

$$\underset{\{m_1^i\}}{\text{Max}} \left[\frac{m_1^i P_1}{\lambda} + \frac{\left[-\frac{m_1^i}{\lambda} + \frac{K_2 h_X \bar{X}}{h_E} - \frac{K_2 K_{1i} \mu}{K_{2i}} + t_i z_i + h_E \left(\mu - \mu_i\right) + \left(\frac{K_2 \left(t + \lambda^2 t^2 h_S\right)}{h_E} - t \right) q \right]^2}{2\left[\left(t_i - t\right) + \frac{K_1 K_2}{h_E}\right]} \right]. \tag{10}$$

The following theorem summarizes equilibrium at $t = 1$.

Theorem 2 *Equilibrium price and allocations at $t = 1$ are characterized by stock price*

$$P_1 = \frac{1}{K_1}\left[h_X\bar{X} + \left(t + \lambda^2 t^2 h_S\right)X - \left(t + \lambda^2 t^2 h_S\right)\frac{S}{\lambda t}\right] \tag{11}$$

and demand

$$m_1^i = \lambda t_i \varepsilon_i + \lambda K_1\left(\mu_i - \mu\right) + \lambda\left(\frac{t_i - t}{K_1}\right)\left[h_X\left(X - \bar{X}\right) + \lambda t h_S S\right] + \left(\frac{K_{1i}}{K_1}\right)S, \tag{12}$$

where $\mu = \int_0^1 \mu_i di$, $t = \int_0^1 t_i di$, $K_{1i} \equiv h_X + t_i + \lambda^2 t^2 h_S$ *and* $K_1 \equiv \int_0^1 K_{1i} di = h_X + t + \lambda^2 t^2 h_S$.

Equation (12) allows us to discuss the impact of dispersion of opinions and information asymmetry on holdings. The higher the precision of private information, the more weight is given to the private shock ε_i. The impact of differences of opinion from the average consensus is a function of the aggregate uncertainty in the economy at $t = 1$.

3.3 Public Announcements, Price Reactions and Trading Volume

In this section, I simplify the model to analyze how changes in information asymmetry and differences of opinion affect aggregate volume, assuming there are just two classes of investors, the informed and uninformed ones. The informed investors comprise a proportion γ of all investors, have beliefs μ_I about the mean of the public signal noise and precision t_I on the private signal received at $t = 1$. The uninformed, in proportion $1 - \gamma$, have beliefs μ_U about the public signal and precision t_U. The private signal observed by the informed agents is more precise than the one possessed by the uninformed, such that $t_I > t_U$. Finally, I also assume, to simplify calculations, that the average opinion about the public signal's noise is zero (i.e., $\mu = 0$), implying that dispersion of beliefs has no impact on prices.

In this case, the following simplifications can be made:

$$\mu \equiv \int_0^1 \mu_i di = \gamma\mu_I + (1-\gamma)\mu_U = \mu_U + \gamma\left(\mu_I - \mu_U\right) = 0, \tag{13}$$

$$t \equiv \int_0^1 t_i di = \gamma t_I + (1-\gamma)t_U = t_U + \gamma\left(t_I - t_U\right), \tag{14}$$

$$K_1 \equiv \int_0^1 K_{1i} di = h_X + t_U + \gamma\left(t_I - t_U\right) + \lambda^2\left[t_U + \gamma\left(t_I - t_U\right)\right]h_S, \tag{15}$$

$$K_2 \equiv \int_0^1 K_{2i} di = h_X + t_U + \gamma\left(t_I - t_U\right) + \lambda^2\left[t_U + \gamma\left(t_I - t_U\right)\right]h_S + h_E. \tag{16}$$

The corollary below summarizes prices and holdings:

Corollary 1 *Suppose investors belong to just two classes: the informed and uninformed. The informed investors, in proportion γ, are characterized by beliefs μ_I and precision t_I of the private signal. The remaining $(1-\gamma)$ proportion of uninformed investors have beliefs μ_U and precision t_U. In this case, holdings of an uninformed investor are given by:*

$$\begin{aligned} m_2^U &= \lambda\left[t_U\varepsilon_i - h_E\left(\mu_U-\nu\right) + \frac{(t_U-t)}{K_2}\left(h_X\left(X-\bar{X}\right)+\lambda t h_S S\right)\right] + \left(\frac{K_{2U}}{K_2}\right)S, \\ m_1^U &= \lambda\left[t_U\varepsilon_i + K_1\mu_U + \frac{(t_U-t)}{K_1}\left(h_X\left(X-\bar{X}\right)+\lambda t h_S S\right)\right] + \left(\frac{K_{1U}}{K_1}\right)S. \end{aligned} \tag{17}$$

When an investor is more optimistic about earnings ($\mu_U > 0 > \mu_I$), she trades on this belief by purchasing relatively more of the asset at date 1. Since this small ex-ante optimism about earnings implies, by construction, a higher ex-post *pessimism* about the asset, she reverts her strategy and sell more at date 2, increasing trading volume around announcements accordingly. The private signal received at $t = 1$ also provides investors with information about earnings, but each investor has its own interpretation because of the μ_i parameter, which affects holdings in equilibrium.

Trading volume between t and $t+1$ is defined as the absolute change in stock holdings over time:

$$Vol_{t+1}^i = \left|m_{t+1}^i - m_t^i\right|, \tag{18}$$

and hence volume around the announcement is given by:

$$\begin{aligned} Vol_2^i &= \left|m_2^i - m_1^i\right| \\ &= \lambda\left|-K_2\mu_i - (t_i-t)\left(P_2-P_1\right)\right|. \end{aligned} \tag{19}$$

Trading volume around announcements is linear on absolute price changes if there is no dispersion of opinions. However, when agents do disagree about the interpretation of public information, this linearity breaks down, in contrast to Proposition 2 of Kim and Verrecchia (1991) but similar to Kim and Verrecchia (1994). Here, differences of opinion affect volume even under symmetric information (i.e., when $t_U = t_I = t$). If earnings announcements are useless to convey new information to investors ($h_E = 0$), there are no price reactions, but agents still change their portfolios due to disagreement about the meaning of the public signal itself.

Since holdings are normally distributed, we can use the following result to compute expected volume:

$$y \sim N(\mu,\sigma^2) \;\Rightarrow\; E\left(|y|\right) = 2n\left(\frac{\mu}{\sigma}\right)\sigma - \mu\left[1-2\Phi\left(\frac{\mu}{\sigma}\right)\right]. \tag{20}$$

with $n(.)$ being the probability density function of a standard normal distribution and $\Phi(.)$ its cumulative density function. The next result summarizes expected trading volume before and around announcements.

Theorem 3 *Let agent i have beliefs μ_i about the mean of public signal's noise, and t_i be the precision of the private signal. Furthermore, let the average belief be $\mu = 0$ and t the aggregate informativeness of private signals. Then, expected trading volume is given by:*

1. *Before announcements:*

$$E\left(Vol_1^i\right) = 2\sigma_1^i n\left(\frac{\mu_1^i}{\sigma_1^i}\right) - \mu_1\left[1 - 2\Phi\left(\frac{\mu_1^i}{\sigma_1^i}\right)\right], \tag{21}$$

with

$$\begin{aligned} \mu_1^i &= E\left(m_1^i - m_0^i\right) = \lambda K_1 \mu_i, \\ \sigma_1^i &= \sigma\left(m_1^i - m_0^i\right) = \lambda\left[t_i + \left(\frac{t_i - t}{K_1}\right)^2 h_X + \left(\frac{1}{K_1}\right)^2\left(\frac{K_{1i}}{\lambda} + (t_i - t)\,\lambda t h_S\right)^2 \frac{1}{h_S}\right]^{\frac{1}{2}}. \end{aligned}$$

2. *Around announcements:*

$$E\left(Vol_2^i\right) = 2\sigma_2^i n\left(\frac{\mu_2^i}{\sigma_2^i}\right) - \mu_2\left[1 - 2\Phi\left(\frac{\mu_2^i}{\sigma_2^i}\right)\right], \tag{22}$$

with

$$\begin{aligned} \mu_2^i &= E\left(m_2^i - m_1^i\right) = -\lambda K_2 \mu_i, \\ \sigma_2^i &= \sigma\left(m_2^i - m_1^i\right) = \lambda\,(t_i - t)\,\sigma\,(P_2 - P_1)\,. \end{aligned}$$

It follows from Equation (22) that expected volume is a function of the mean and standard deviation of the change in holdings over time. As fundamental risk grows (i.e., h_X falls), investors are more worried about information asymmetry since the relative difference in the quality of private signals rises. This reduces speculation based on differences of opinion, leading to smaller trading volume.

Now, I present derivatives of expected volume given mean-preserving spreads in asymmetric information or differences of opinion. These spreads are such that a decrease in the quality of information t_U observed by uninformed traders is matched by a proportional increase in t_I for informed ones, in order to keep the aggregate informativeness of private signals constant. It is important to keep t constant to fix the average uncertainty level in the economy, keeping prices constant and allowing me to focus on relative differences between classes.

Theorem 4 *Let agent i have belief μ_i about the public signal's noise mean and let t_i be the belief about the private signal's noise precision. Furthermore, let the average belief be $\mu = 0$ and the aggregate informativeness t of private signals a positive constant. Then, the sign of the derivative of expected volume with respect to μ_i is positive if and only if μ_i is positive, both before announcements and around announcements. Furthermore, the derivative of expected volume with respect to the precision of private signals t_i is always positive both before and around announcements. The analytical formulas are shown below:*

1. *Before announcements:*

$$\left.\frac{\partial E\left(Vol_1^i\right)}{\partial \mu_i}\right|_{\mu=0} = -2\lambda K_1\left[\frac{1}{2} - \Phi\left(\frac{\lambda K_1 \mu_i}{\sigma_1^i}\right)\right] > 0 \Leftrightarrow \mu_i > 0, \tag{23}$$

$$\left.\frac{\partial E\left(Vol_1^i\right)}{\partial t_i}\right|_{fixed\, t} = 2n\left(\frac{\lambda K_1 \mu_i}{\sigma_1^i}\right) * \left.\frac{\partial \sigma_1^i}{\partial t_i}\right|_{fixed\, t} > 0 \textit{ for all } t_i > 0. \tag{24}$$

2. *Around announcements:*

$$\left.\frac{\partial E\left(Vol_2^i\right)}{\partial \mu_i}\right|_{\mu=0} = -2\lambda K_2\left[\frac{1}{2} - \Phi\left(\frac{\lambda K_2 \mu_i}{\sigma_2^i}\right)\right] > 0 \Leftrightarrow \mu_i > 0, \tag{25}$$

$$\left.\frac{\partial E\left(Vol_2^i\right)}{\partial t_i}\right|_{fixed\, t} = 2\lambda n\left(\frac{-\lambda K_2 \mu_i}{\sigma_2^i}\right)\sqrt{Var\left(P_2 - P_1\right)} > 0 \textit{ for all } t_i > 0. \tag{26}$$

Although the theorem above computes derivatives for individual investors, empirical researchers most of the time only have access to aggregate trading volume measures. Thus, it is crucial to derive how increases in dispersion affect aggregate expected volume.

Theorem 5 *Let μ_U define the belief about mean public signals noise by uninformed investors and μ_I the equivalent belief for informed investors such that the average belief is zero, i.e., $\mu \equiv \gamma\mu_I + (1-\gamma)\mu_U = 0$. Then, a mean-preserving rise in differences of opinion, increases trading volume both before announcements and afterwards. Furthermore, a mean-preserving increase in information asymmetry decreases trading volume after announcements.*

An increase in dispersion is equivalent to an increase in $|\mu_U - \mu_I|$.[4] As seen from equation (A.35) and (A.36) in the appendix, we can observe how higher dispersion leads to higher trading at both trading dates. They also show that the magnitude of this increased trading depends on information asymmetry, which has the interesting empirical implication that trading volume varies asymmetrically with dispersion. The theorem crucially depends on the result that the cumulative probability function of a normal variable is a monotonically increasing function of its mean. On the other hand, when I compute the total differential with respect to information asymmetry, the resulting formulas are functions of the probability density functions instead, preventing me from finding a clear sign for the derivative of total volume before announcements. However, it can still be shown that trading volume after announcements is unambiguously lower following an increase in information asymmetry.

Given these results, it is important to outline some limitations of the model. The three-period CARA setting imposes unrealistic constraints upon agents, who might prefer to smooth their trading both before and after announcements as uncertainty is resolved [see for example He and Wang (1995) or Makarov and Rytchkov (2006)]. Furthermore, agents only trade in two periods, with volume at $t = 1$ depending on the initial allocations of each investor. In a dynamic model, expected volume at $t = 1$ would certainly be higher due to a change in holdings at $t = 0$.

Another important assumption is that differences of opinion are constant over time. For example, companies might release their earnings while, at the same time, give further clarification to the market on how particular figures have been calculated, reducing differences of interpretation. Although this would affect the magnitude of the derivatives above, it is unlikely to change their signs.

Regardless of these limitations, the model captures the main motives for trading and expands the literature by incorporating more realistic features than previous ones. In the next sections I test the model on stock turnover near earnings announcements and show that while the model can reasonably match patterns associated with trading levels, it cannot match the evidence found in the data for the sensitivity of the difference in trading around and trading before announcements with respect to differences of opinions. The empirical findings I present in the next sections also

[4] As $\mu = 0$, whenever one class of investors has positive expectations about the signal, the other has negative expectations by construction.

illustrate the usefulness of the model to examine how stock turnover relates to pre-event measures of asymmetric information and differences of opinion.

4 Hypotheses

In light of these ideas, corporate earnings announcements constitute prime candidates for empirical investigation, since they convey important information about firm value at scheduled dates known by all traders in advance. In particular, I test the following hypotheses:

Hypothesis 1 *Trading volume before earnings announcements increases with dispersion of opinions.*

The larger is the disagreement among investors the more willing to speculate on the outcome of announcements they become. Although agents are well aware that other market participants might have access to more precise information, they are still willing to bet on their individual beliefs regardless of possible informational disadvantages. Ultimately, this leads to an increase in trading volume before announcements following rises in dispersion, as shown by equation (A.35) in the appendix.

Hypothesis 2 *Trading volume around earnings announcements increases with dispersion of opinions.*

Equation (A.36) in the appendix shows that a rise in dispersion always increases trading volume after announcements. Aggregate uncertainty decreases from $t = 1$ to $t = 2$ because extra information is released to the market. Agents are therefore more willing to trade upon differences in beliefs as time elapses and uncertainty about the liquidation value is reduced.

A positive relationship between turnover around earnings announcements and analyst forecast dispersion has been explored many times before [Ajinkya, Atiase, and Gift (1991) or Bamber, Barron, and Stober (1997)], but I control for differences in information asymmetry and provide evidence that the magnitude of this effect itself depends on information asymmetry. This illustrates that dispersion of analysts' forecasts must be used with care if one does not account for adverse selection costs.

Hypothesis 3 *Investors trade less before announcements if information asymmetry is high.*

At the first trading date, equation (24) shows that an increase in the quality of private signals always increases expected trading volume, regardless of whether the investor is better or worse informed than the average. An increase in information asymmetry is characterized by a fall in the quality of uninformed agents' private signals and a proportional rise in the quality of private signals observed by informed agents. This fall on the uninformed's signal quality makes them trade less (the "fear of trading" effect), while the corresponding increase on the informed's signal quality makes these investors trade more. The information gap between informed and uninformed traders determines whether aggregate trading volume goes up or down, and explains why its sign is ambiguous following a mean-preserving rise in information asymmetry. This result may explain why stock turnover before announcements can be actually lower after decreases in information asymmetry, exactly the results found by Bailey, Karolyi, and Salva (2005) for international firms that cross-list their shares in US stock exchanges via American Depositary Receipts (ADRs).

Chae (2005) essentially tests this hypothesis, investigating turnover reactions rather than levels of trading; using market capitalization, analyst coverage and average bid-ask spreads as proxies for information asymmetry. In this paper, I use a more direct proxy for asymmetry borrowed from the microstructure literature, the probability of information-based trading (PIN) [Easley, Kiefer, and O'Hara (1996), Vega (2006)] and show that it is negatively related to turnover before announcements.

Hypothesis 4 *Investors trade less around announcements when information asymmetry is high.*

Equation (26) shows that a fall in the quality of private signals always decreases expected volume around announcements. The change in aggregate expected trading volume depends on whether, at the margin, uninformed investors are more or less sensitive than informed ones after an increase in asymmetry. Whether it decreases or increases trading around announcements across firms is for the data to uncover. In particular, I use PIN to test this hypothesis, showing that turnover levels after announcements are negatively related to asymmetry around earnings announcements.

None of the four hypotheses say anything about the timing of trades, i.e., the trading date at which investors place their orders. The scheduled release of public information affects investors' trading decisions, who shift their trading depending on information asymmetry and dispersion. The model allow us to test the following hypothesis:

Hypothesis 5 *Turnover around announcements increases relative to turnover before announcements when information asymmetry and dispersion are high.*

Investors have more incentives to wait for the release of public signals when information asymmetry is high, since these signals reduce the wedge between informed and uninformed investors. The fear of trading with informed agents makes uninformed ones prefer to wait for as much information as possible, leading to relatively more trading around announcements compared to before announcements when there is more information asymmetry among agents. If agents disagree about how to interpret the information released by public announcements, the model implies that they will speculate more on their differential interpretations after the public signal is released. The reduction in uncertainty due to the release of public information makes everyone more willing to trade on their differential valuations, even though an investor is aware she could be trading with better-informed ones.

In the empirical section, I show evidence against the hypothesis that higher dispersion delays trading until after the announcement. In fact, there is strong evidence in the opposite direction, in the sense that higher dispersion *accelerates* trading. The assumption that investors can only trade once before the public signal is released imposes big constraints on how investors can react to differences of opinion, since holdings at $t = 1$ affect volume before and around announcements. If the announcement itself conveys information that reduces the disagreement of interpretations among investors, it might also lead to relatively less trading afterwards. The private signal observed at $t = 1$ provides information about the earnings announcement itself. As these earnings also affect future prices and trading decisions, the heterogeneous information processing among agents will affect holdings.

5 Empirical Results

5.1 Data Description

The data comprise all annual earnings announcements from the Institutional Brokers Estimate System (I/B/E/S) for the period running from 1984 to 2002. These events are matched to with CRSP to get price and volume data. I further restrict the sample using two criteria. First, I only include I/B/E/S events with primary annual earnings-per-share (EPS) forecasts made by at least three analysts. Second, I remove forecasts made after the reporting date of earnings and only include firms with at least 30 days of return data available during the estimation window period covering $t = -80$ to $t = -11$ trading days before the announcement.

I measure dispersion as the standard deviation of unadjusted analyst forecasts reported by I/B/E/S divided by average stock price observed during the estimation period [Qu, Starks, and Yan (2004)]. Given the biases in I/B/E/S data uncovered by Diether, Malloy, and Scherbina (2002), I use the Unadjusted Summary file to compute dispersion measures.[5] The implicit assumption is that dispersion of analysts' earnings forecasts captures investors' differences of opinion.

Dispersion is also affected by the amount of pre-announcement information known by agents and the fundamental uncertainty about the stock. In the model, dispersion of forecasts among investors is caused by two factors: differential updating of beliefs after observing private signals and the heterogeneous opinions that each investor has about the outcome of the public signal.

More generally, the level of uncertainty about liquidation values and the relative precision of private information signals affect forecasts [see for example Abarbanell, Lanen, and Verrecchia (1995)]. Given a fixed value of private signals' average uncertainty, uninformed investors will trade less as information asymmetry increases to avoid being exploited by others with access to more precise private information. Empirically, I proxy for this adverse-selection cost with the probability of information-based trading (PIN) in the calendar year prior to the reporting date of earnings. This measure was developed by Easley, Kiefer, and O'Hara (1996) and is computed from a structural market-microstructure model based on a stock's total number of daily buy and sell transactions in a given calendar year. It has been used to explain many information-related effects observed in

[5]Qualitative results are the same regardless of whether data come from Summary or Detailed files, though statistical significance decreases a little when using the former.

stock returns and volatility series [see for example Easley, Hvidkjaer, and O'Hara (2002); Vega (2006)] and it serves as my control for the private information component embedded in analysts' forecast dispersion.[6] The exclusion of NASDAQ-listed companies reduces the number of PIN-matched events by more than 40%, biasing the sample towards larger and more widely covered firms, leaving a total of 20,403 earnings announcements events from 2,730 firms. Following Hong, Lim, and Stein (2000), I also use the logarithm of market capitalization and analyst coverage as further controls for information asymmetry. Finally, I reduce the impact of outliers in turnover and dispersion measures by "winsorizing" them at the 1% level.[7]

In Panel A of Table 1, I show descriptive statistics of events with available PIN estimates. Announcements rarely exhibit high levels of disagreement, with mean dispersion being equal to 0.56% of share price and standard deviation equal to 1.22%. Most stocks in the sample also exhibit small values for PIN but its distribution exhibits less kurtosis and skewness than what is found for dispersion. The correlations among explanatory variables are in line with prior expectations: Panel B shows that PIN is negatively related to firm size and analyst coverage, matching the intuition that investors face a smaller probability of trading with informed investors for stocks with higher degrees of public information disclosure. Dispersion is highly correlated with stock volatility, showing the importance of controlling for fundamental uncertainty when attempting to evaluate the impact of dispersion of opinions. The table also shows that higher analyst coverage is associated to a smaller dispersion of forecasts. However, unreported results show that once we control for firm size (like Hong, Lim, and Stein (2000)), there is a negative correlation between residual coverage and forecast dispersion. This is evidence in favor of higher coverage reducing information asymmetry and increasing disagreement among investors.

5.2 Event-study and Regression Analysis

The hypotheses are tested on average stock turnover before earnings announcements, around earnings announcements and the difference between the two.[8] The distributional characteristics of raw turnover and the fact that it is bounded below at zero cause large departures from normality. Follow-

[6] Data with estimated PIN measures of NYSE/AMEX common stocks from 1983 to 2003 can be obtained from Soeren Hvidkjaer's site at http://www.smith.umd.edu/faculty/hvidkjaer/data.htm

[7] Results are qualitatively the same with a 5% or 10% cut-off level.

[8] I use the terms Around and After interchangeably.

ing Ajinkya and Jain (1989), I apply the logarithmic transformation to make the turnover distribution better behaved. Thus, daily log turnover $\tau_{i,t}$ is defined as:

$$\tau_{i,j} = \log\left(0.001 + \frac{\text{Shares traded on day t}}{\text{Shares outstanding for firm j on day t}}\right).$$

The amount of trading *before* an announcement, *around* an announcement and the turnover difference are defined, respectively, as:[9]

$$\tau_{i,j}^{B} = \frac{\sum_{t=-10}^{t=-3}(\tau_{i,t})}{8}, \quad (27)$$

$$\tau_{i,j}^{A} = \frac{\sum_{t=-2}^{t=2}(\tau_{i,t})}{5}, \quad (28)$$

$$\tau_{i,j}^{Diff} = \tau_{i,j}^{A} - \tau_{i,j}^{B}. \quad (29)$$

Figure 2 shows large differences in turnover reactions between firms with and without PIN estimates. It contains the relative amount of trading in each event-day compared to benchmark levels of trading when sample is split according to whether PIN is available or not. I use a 70-day estimation window as benchmark turnover and compute daily abnormal reactions during the [-10,10] days period near announcements. Unreported statistics show that firms without PIN tend to be smaller, less liquid, more volatile and to have a smaller analyst following than those with PIN. Firms with PIN have higher levels of abnormal trading before announcements, but after earnings are released the increase in turnover is much larger for firms without PIN. The reduction in cross-sectional variability caused by the restriction that firms must have PIN estimates makes testing the hypotheses more difficult, but results are still economically significant.

Panel C of Table 1 shows descriptive statistics for log turnover measures. Average turnover is larger both before announcements and around announcements when compared to the estimation period. The skewness and kurtosis are much closer to normal values showing that the log transformation takes care of concerns about the statistical distribution of the dependent variables. Although averages relative to pre-event daily turnover may not seem economically large, they are equivalent to a 1.2% increase on the days before the announcement and a 35.9% on the days around the announcement. Both increases are statistically significant at the 1% level. The increase in turnover

[9] Results are the same when I change the definition of the "around announcements" window to $[-1, 1]$ days.

before announcements for firms with PIN estimates contrasts with the -3.82% found for the whole sample, being close to the one reported by Chae (2005). The difference relative to positive value found in the sample constrained by PIN availability can be explained by the absence of NASDAQ firms, which have turnover before announcements 4.73% lower, on average, than during the estimation period. The distribution of the differences in turnover is highly skewed (equal to 2.9 for the whole sample) and explains how the fact that almost 30% of all earning announcements exhibit larger turnover before versus turnover around announcements are compatible with the results seen on Figure 2. During the empirical analysis, I perform robustness tests to account for possible selection-bias due to this constraint due to PIN availability and show that my results are unchanged.

I test hypotheses 1 and 3 by looking at how turnover before earnings announcements is affected by proxies for dispersion and asymmetric information. Table 2 presents results for different specifications. The first hypothesis states that trading before announcements increases with dispersion of opinions. The univariate regression coefficient of turnover on dispersion equals 0.39 but is not statistically significant which, at first, is evidence against the hypothesis. However, once I control for information asymmetry using PIN, dispersion coefficients increase and become statistically significant. This shows the relevance of controlling for the private information component embedded in analyst forecast dispersion, specially if researchers intend to use it as a proxy for differences of opinion.

Hypothesis 3 predicts that trading before announcements is negatively related to information asymmetry and I cannot reject it at the 99% confidence level across all specifications. We can also observe that controlling for the amount of news is very important to explain trading levels. Using average absolute abnormal returns to proxy for firm-specific information and absolute abnormal market returns to proxy for market-wide information, we can see that both are positively related to turnover and highly significant, similar to previous findings [Chae (2005)]. The most significant drivers of trading volume are the amount of news hitting the stock during the event, either firm-related or market-related.

I also test if the relationship between dispersion and turnover is concave in PIN, i.e., the larger information asymmetry levels are for a given stock, the smaller impact dispersion has on turnover. This conjecture cannot be rejected in the data, with the coefficient on the DISP*PIN cross-product being equal to -42.62 and statistically significant.

Adding firm size and analyst coverage as additional controls do not affect the significance of dispersion and PIN, although estimated PIN parameters do become smaller in magnitude. This decrease in PIN coefficients is expected, since these control variables also capture part of information asymmetry differences across firms. The positive coefficients for analyst coverage in columns 6 to 8 are associated both with less information asymmetry and more dispersion of forecasts, in line with Hong, Lim, and Stein (2000) and Brown and Hillegeist (2003).

The information contained in announcements also affects trading volume after the release of signals. I use abnormal turnover around announcements as the dependent variable to test hypotheses 2 and 4. The public information release helps to level off differences of information across investors, enticing them to wait for its outcome before placing their order. In Table 3, I re-estimate regressions. If we look at the coefficient estimated for dispersion in column 6 of table 3, it is equal to 6.06. This supports hypothesis 2, which states that turnover around announcements is also positively related to dispersion.[10]

Furthermore, just as predicted in hypothesis 4, turnover around announcements is negatively related to PIN, having a coefficient equal to -3.39. Although the derivatives of expected turnover with respect to information asymmetry depend on chosen parameters, this negative signal gives evidence that the decrease on uninformed traders' demands is larger than the increase on uninformed's demands following an increase in asymmetry.

The results above support the claim that analyst dispersion measures differences of opinion rather than uncertainty. Higher uncertainty about asset value reduces trading and if dispersion was truly a proxy for uncertainty, we would not have found the estimated coefficients.

The difference in parameters estimated for turnover before and turnover around announcements suggests that they are not only related to levels of trading, but also to the timing of trades with respect to releases of public information. This forms the basis of hypothesis 5 and I provide evidence to support it by running regressions using the difference between turnover around and turnover before announcements as the dependent variable. Results in Table 4 show that the difference in turnover is positively related to information asymmetry, but negatively related to dispersion. This provides a new way to disentangle the relationship between differences of opinion and information asymmetry and adds another feature that must be captured by trading behavior models. They should not only

[10] I use the specification contained in column 6 as the main focus of analysis unless otherwise noted.

match cross-sectional differences in levels of trading, but also time-series differences.

Higher asymmetry increases the fear of trading with uninformed investors and decreases trading in both periods as can be seen in Tables 2 and 3. Since public signals reduce the wedge between informed and uninformed investors, hypothesis 5 predicts relatively more trading after announcements for higher levels of asymmetry. The estimated PIN coefficient is equal to 0.37 and supports this claim, being statistically significant at the 5% level.

Hypothesis 5 also states that there should be relatively more trading after announcements when disagreement among investors is high. The estimated coefficient associated to dispersion equals -1.70, which rejects the model's prediction. Higher dispersion of opinions in fact accelerates trading, making investors speculate on their beliefs before earnings are released. This provides further evidence in favor of seeing forecast dispersion as a measure of differences of opinion [Diether, Malloy, and Scherbina (2002)] rather than a measure of fundamental uncertainty [Johnson (2004)].

After observing these results, the natural question is whether changes in PIN and dispersion lead to economically significant changes in turnover. In Table 5, I take estimated parameters and show the impact on expected turnover before announcements, after announcements and their difference, following a one standard deviation increase in three variables: PIN, dispersion and analyst coverage. In Panel A, we see that differences of opinion have a smaller impact on turnover than information asymmetry. Increasing dispersion raises daily turnover before announcements by 0.12 standard deviations (an increase of 6.49% relative to its average), corresponding to an extra $7.88mi in dollar volume for the average firm during the 8-day period before the event. The same one standard deviation variation in PIN reduces turnover by 0.13 standard deviations (equivalent to a -6.98% decrease relative to its unconditional mean). In Panel B, I repeat these calculations but examine turnover around announcements. A one-sigma increase in PIN decreases turnover by 0.1 standard deviations (-6.76% of its mean), less than the reduction found before announcements. Furthermore, following a one standard deviation increase in dispersion, turnover around announcements decrease by 0.09 standard deviations (5.98% of its mean), also less than the variation observed before announcements.

I examine whether these differences across time are economically significant in Panel C, where I compute the effect on the difference between turnover around and before the event. A one standard deviation increase in PIN makes the difference in turnover go up by 0.04 standard deviations on average, a number seemingly small at first but that corresponds to a 8.29% increase relative to the mean difference. Similar variation is found for a change in dispersion, which decreases turnover by 0.04 standard deviations and corresponds to -8.50% of the mean turnover difference for the whole sample. These results are strong evidence that releases of public information have a significant impact on the timing of trades and these results follow the direction predicted by hypothesis 5.

Increasing analyst coverage by one standard deviation has the largest impact on trading levels, raising turnover both before and around announcements by about 15-20%, but it does not seem to affect the timing of trades, with the -0.108 estimated coefficient not significantly different from zero.

A crucial issue is whether the results above are driven by sample-selection bias due to the availability of PIN measures. Although in Column (8) of Tables 2-4 I estimate regressions using a dummy variable controlling for the availability of PIN, the PIN sample might be a non-random sample of US firms. This would lead to the classic sample selection problem described by Heckman (1979), who shows how OLS estimates are biased if stock characteristics conditional on PIN availability are different than for the average US company. Out of the 28,628 earnings announcements extracted from I/B/E/S, data on PIN are available for only 19,690 events. Those excluded from the regressions include 3,627 announcements from NYSE/AMEX-listed firms (19.15% of the total number of excluded events) and 17,891 from NASDAQ-listed firms (the remaining 80.85%). Unavailability of PIN estimates for NYSE/AMEX-listed firms is mainly caused by data constraints imposed by Easley, Hvidkjaer, and O'Hara (2002) to ensure reliable estimation of the model. More important, the exclusion of NASDAQ-listed firms occurs mainly due to the market microstructure of the exchange. The structural model in Easley, Kiefer, and O'Hara (1996) is based on an uninformed market-maker setting that is much closer to the trading environment seem on the NYSE and AMEX, with PIN estimates only being computed for NYSE/AMEX firms.

In Panel A of Table 6 I test the difference in average turnover measures, dispersion and size between PIN and no-PIN firms. Firms with PIN estimates available have smaller turnover before, turnover around and turnover difference, but tend to be smaller in size and to have less dispersion of opinions. All these differences are significant at the 1% significance level. These differences indicate a potential selection bias if we only use PIN firms in the regressions and extrapolate the conclusions to average US firm.

I control for possible selection-bias using the Heckman (1979) two-step model. The first-step comprises in estimating a probit regression on the likelihood that a firm has PIN estimates available in the previous year. As controls, I include analyst forecast dispersion, market capitalization, analyst coverage, firm-age (defined as current year minus the first year of stock data available in CRSP), institutional ownership (fraction of the firm owned by institutional investors based on 13f Holdings data), number of institutional investors, the standard deviation of returns during the 200-day estimation period, aggregate stock market turnover and a dummy variable controlling for Nasdaq membership (based on CRSP's HEXCD variable). The second-step comprises of estimating the specification in Column (6) of Tables 2 to 4, but now including the Mills ratio (λ) as an additional variable to control for selection bias. In Panel B of Table 6, I present the results for both steps. As expected, the likelihood of having PIN estimates available is positively related with size, dispersion, analyst coverage, firm age and the fraction of institutional investors' ownership. We also find that Nasdaq membership and the standard deviation of returns is negatively related to PIN-availability. The Pseudo-R^2 of this regression is equal to 63.42%, displaying a good degree of explanation.

In the second-step, the statistical significance of the Mills ratio shows how selection-bias is an issue. However, all the signs estimated for PIN and dispersion remain significant and with the same signs as before. For example, when we compare the regression for the difference in stock turnover with the one estimated in Column (6) of Table 4, we can see that the estimated parameter for PIN decreases from 0.368 to 0.327, while the coefficient for dispersion goes from -1.705 to -1.635. These estimates show that the results are not driven by sample selection.

5.3 Additional Robustness Checks

I now subject the results to a number of robustness checks to verify that they are not due to a particular sample or methodology I use. I repeat the analysis using quarterly earnings announcements, a different estimation-period window, raw turnover measures instead of log turnover and, finally, I split the sample in half.

In Panel A of table 7, I estimate regressions using quarterly earnings announcements, changing the estimation period window to [-30,-11] days before events to avoid overlaps with announcements in the previous quarter. Using quarterly data increase the number of events and slightly decrease the number of firms in the sample. The parameters for PIN and dispersion are significant in all cases and yield similar qualitative results to estimates based on annual data. Most important for robustness, parameters for PIN and dispersion in the turnover differences regression (the "Diff" column) are remarkably similar to the ones estimated in column (6) of Table 4.

In all previous regressions, I've used [-2,2] days around an announcement as the "Around" event-period. As an additional check, I re-estimate regressions using [-1,1] as the length of the "Around" period. Results, shown in Panel B of table 7, are broadly similar to the baseline regressions.

Finally, I split the annual events sample in two halves: one with data from 1984–1993 and the other from 1994-2002. Results in Table 8 show that the significance of results comes mostly from the second half of the sample. The larger R^2s found for all three different dependent variables during the 1994–2002 period can be explained by greater attention being given to analyst recommendations following the spread of the Internet and improvements on how information is propagated across financial markets.

6 Conclusion

This paper examines turnover measures to quantify the impact of differences of opinion and information asymmetry on trading behavior. In particular, I try to explain why many firms have high turnover before earnings announcements relative to turnover at the time they are released. At first, this might seem puzzling, since risk-averse, uninformed investors would prefer to trade relatively more after the release of information, when they face a smaller probability losing money to investors with access to superior information. However, if investors disagree about the meaning of public information, their willingness to trade before announcements increases. This corresponds to the "agreeing-to-disagree" assumption [see Harrison and Kreps (1978), Kandel and Pearson (1995) or Banerjee and Kremer (2005)] and I use it to explain the cross-sectional turnover differences, showing not only that levels but also the timing of trades are affected by disagreement in interpreting public information.

I propose a rational-expectations model in which agents who receive private information of asymmetric quality trade a risky security before and after observing a public signal. I derive analytical formulas for expected trading volume and show that higher dispersion increases expected aggregate turnover both before announcements and around them. An increase in information asymmetry decreases trading before announcements by uninformed investors, but the aggregate effect depends on how much extra trading is soaked up by relatively better informed ones. After announcements, increases in asymmetry unambiguously decrease aggregate trading volume.

Empirically, I use earnings announcements data of US firms to test predictions about stock turnover before and around announcements. I find that a one standard deviation increase in dispersion accelerates trading, reducing the difference between turnover around and turnover before announcements by 8.50%. A similar increase in PIN delays trading, raising the difference by 8.29%. Examining cross-sectional differences in turnover over time uncover patterns that must be explained by trading behavior models and provides researchers with a new way to test the usefulness of proxies for information asymmetry and differences of opinion. Simply extending three-period volume models to incorporate differential interpretations of public signals (similar to Kandel and Pearson (1995)) cannot explain the time-series differences in turnover before and turnover around earnings announcements.

My results provides new evidence that analysts' forecast dispersion is more closely related to differences of opinion [Diether, Malloy, and Scherbina (2002)] rather than to a measure of fundamental uncertainty [Johnson (2004)] and are robust to the periodicity of announcements (quarterly or annual), sample periods and length of the "Around" announcements period window.

The combination of changes in dispersion and information asymmetry help to explain why some stocks actually have higher abnormal turnover before announcements, a characteristic of about one third of events in my sample. Any model that attempts to explain trading volume must be able to explain these cross-sectional differences in turnover, on top of any explanation about trading levels, i.e. the timing of trades is also important.

Appendix

Proof of Theorem 1. First-order conditions derived from equation (5) are:

$$\begin{aligned} m_2^i &= \lambda \left(\frac{E_i\left[\widetilde{X} \mid \mathcal{F}_2^i\right] - P_2}{Var\left[\widetilde{X} \mid \mathcal{F}_2^i\right]} \right) && \text{(A.1)} \\ &= \lambda \left[\frac{\frac{h_X\bar{X}+h_E(E-\mu_i)+t_iZ_i+\left(\frac{h_S}{\xi^2}\right)q}{h_X+t_i+h_E+\frac{h_S}{\xi^2}} - P_2}{\frac{1}{h_X+t_i+h_E+\frac{h_S}{\xi^2}}} \right] \\ m_2^i &= \lambda \left[h_X\bar{X} + h_E\left(E-\mu_i\right) + t_iZ_i + \left(\frac{h_S}{\xi^2}\right)q - K_{2i}P_2 \right]. && \text{(A.2)} \end{aligned}$$

Market-clearing implies:

$$\begin{aligned} S &= \int_0^1 \lambda \left[h_X\bar{X} + h_E\left(E-\mu_i\right) + t_iZ_i + \left(\frac{h_S}{\xi^2}\right)q - K_{2i}P_2 \right] di, && \text{(A.3)} \\ \frac{S}{\lambda} &= h_X\bar{X} + h_E\left(E-\mu\right) + tX + \left(\frac{h_S}{\xi^2}\right)q - K_2P_2. && \text{(A.4)} \end{aligned}$$

with $t \equiv \int_0^1 t_i di$, $\mu \equiv \int_0^1 \mu_i di$, $K_2 \equiv h_X + t + h_E + \frac{h_S}{\xi^2}$. The term $\int_0^1 t_i\varepsilon_i di$ vanishes by the law of large numbers. Isolating P_2 and using the definition of q in equation (3) leads to:

$$P_2 = \frac{1}{K_2}\left[h_X\bar{X} + h_E\left(E-\mu\right) + \left(t + \frac{h_S}{\xi^2}\right)X - \left(\frac{1}{\lambda} + \frac{h_S}{\xi}\right)S \right]. \qquad \text{(A.5)}$$

Given our linear conjecture $P_2 = \phi_2 + \alpha_2\bar{X} + \beta_2X - \gamma_2S + \theta_2E$, we match coefficients and obtain:

$$\phi_2 = \frac{-h_E\mu}{K_2},\ \alpha_2 = \frac{h_X}{K_2},\ \beta_2 = \frac{t+\frac{h_S}{\xi^2}}{K_2},\ \theta_2 = \frac{h_E}{K_2} \text{ and } \gamma_2 = \frac{\frac{1}{\lambda}+\frac{h_S}{\xi}}{K_2}.$$

Finally:

$$\xi = \frac{\gamma_2}{\beta_2} = \frac{\frac{1}{\lambda}+\frac{h_S}{\xi}}{t+\frac{h_S}{\xi^2}} \Longrightarrow \xi = \frac{1}{\lambda t}. \qquad \text{(A.6)}$$

Thus, prices at $t = 2$ are given by:

$$P_2 = \frac{1}{K_2}\left[h_X\bar{X} + h_E\left(E-\mu\right) + \left(t + \lambda^2t^2h_S\right)X - \left(\frac{1}{\lambda} + \lambda th_S\right)S \right]. \qquad \text{(A.7)}$$

Now, we plug these prices back in equation (A.2) to get demands:

$$m_2^i = \lambda K_{2i}\left(\frac{h_X\bar{X}+h_E(E-\mu_i)+t_iZ_i+\lambda^2t^2h_Sq}{h_X+t_i+h_E+\frac{h_S}{\xi^2}}-P_2\right),$$

$$\frac{m_2^i}{\lambda} = t_i\varepsilon_i+h_E(\mu-\mu_i)+\left[(t_i-t)-\frac{(t_i-t)\left(t+\lambda^2t^2h_S\right)}{K_2}\right]X+\left[\frac{1}{\lambda}-(t-t_i)\frac{\left(\frac{1}{\lambda}+\lambda th_S\right)}{\lambda K_2}\right]S$$

$$+\frac{(t-t_i)h_X\bar{X}}{K_2}+\frac{(t-t_i)h_E}{K_2}(X+v-\mu),$$

$$m_2^i = \lambda t_i\varepsilon_i+\lambda h_E(\mu-\mu_i)+\frac{\lambda(t_i-t)}{K_2}\left[h_X\left(X-\bar{X}\right)-h_E(v-\mu)+\lambda th_SS\right]+\frac{K_{2i}}{K_2}S \qquad \text{(A.8)}$$

■

Proof of Theorem 2. By the properties of the log-normal distribution, the conditional expectation inside the brackets of equation (3.2) is given by:

$$E^i\left[-e^{-\left[\frac{1}{\lambda}m_1^i\left(\widetilde{P_2}-P_1\right)+\left(E_i\left[\widetilde{X}|\mathcal{F}_{i2}\right]-\widetilde{P_2}\right)\left(\widetilde{X}-\widetilde{P_2}\right)K_{2i}\right]}\mid\mathcal{F}_{i2}\right]$$

$$= -e^{\left[-\frac{1}{\lambda}m_1^i\left(\widetilde{P_2}-P_1\right)-\frac{K_{2i}\left(E_i\left[\widetilde{X}|\mathcal{F}_{i2}\right]-\widetilde{P_2}\right)^2}{2}\right]}$$

$$= -e^{\left[\frac{1}{\lambda}m_1^i\left(P_1-\widetilde{P_2}\right)-\frac{K_{2i}\left[\frac{t_iZ_i-tq+h_E(\mu-\mu_i)+(t-t_i)\widetilde{P_2}}{K_{2i}}\right]^2}{2}\right]}. \qquad \text{(A.9)}$$

In the expression above, we are only left with uncertainty from P_2. Since agents are no longer myopic, different opinions about the public signal make them have different expectations about future prices:

$$E^i\left\{-e^{\left[\frac{1}{\lambda}m_1^i\left(P_1-\widetilde{P_2}\right)-\frac{\left(t_iZ_i-tq+h_E(\mu-\mu_i)+(t-t_i)\widetilde{P_2}\right)^2}{2K_{2i}}\right]}\mid\mathcal{F}_{i1}\right\}$$

$$= -\int\frac{1}{\sqrt{\frac{2\pi}{K_{2i}}}}exp\left[\begin{array}{c}\frac{1}{\lambda}m_1^i\left(P_1-\widetilde{P_2}\right)-\frac{\left(t_iZ_i-tq+h_E(\mu-\mu_i)+(t-t_i)\widetilde{P_2}\right)^2}{2K_{2i}}\\-\frac{1}{2}\frac{K_{1i}(K_2)^2}{h_EK_{2i}}\left[\widetilde{P_2}-\frac{\left(K_{2i}h_X\bar{X}-K_{1i}h_E(\mu-\mu_i)+h_Et_iZ_i+\left[sK_{1i}+\lambda^2t^2h_SK_{2i}\right]q\right)}{K_{1i}K_2}\right]^2\end{array}\right]d\widetilde{P_2}.$$

with $K_{1i}\equiv Var(X\mid Z_i,P_1)=h_X+t_i+\lambda^2t^2h_S$.

Omitting the terms unrelated to m_1^i and $\widetilde{P_2}$ we see that the expectation is proportional to:

$$
\begin{aligned}
&\propto \quad -\int exp\left[\begin{array}{c} \frac{1}{\lambda}m_1^i\left(P_1-\widetilde{P_2}\right)-\frac{(t_iZ_i+h_E(\mu-\mu_i)-tq)(t-t_i)\widetilde{P_2}}{K_{2i}}-\frac{\left[(t-t_i)\widetilde{P_2}\right]^2}{2K_{2i}} \\ -\frac{1}{2}\frac{K_{1i}(K_2)^2}{h_EK_{2i}}\left[\widetilde{P_2}^2-\frac{2\widetilde{P_2}\left(K_{2i}h_X\bar{X}-K_{1i}h_E(\mu-\mu_i)+h_Et_iZ_i+\left[tK_{1i}+\lambda^2t^2h_SK_{2i}\right]q\right)}{K_{1i}K_2}\right]\end{array}\right]d\widetilde{P_2} \\
&\propto \quad -e^{\left[\frac{1}{\lambda}m_1^iP_1+\frac{\left(-\frac{1}{\lambda}m_1^i+A\right)^2}{2\left[\frac{(t-t_i)^2}{K_{2i}}+\frac{K_{1i}(K_2)^2}{h_EK_{2i}}\right]}\right]}\times\int e^{\left[-\frac{1}{2}\left[\frac{(t_i-t)^2}{K_{2i}}+\frac{K_{1i}(K_2)^2}{h_EK_{2i}}\right]\left\{\widetilde{P_2}-\frac{-\frac{1}{\lambda}m_1^i+A}{\frac{(t_i-t)^2}{K_{2i}}+\frac{K_{1i}(K_2)^2}{h_EK_{2i}}}\right\}^2d\widetilde{P_2}\right]}
\end{aligned}
$$

with $A=\frac{(t_iZ_i+h_E(\mu-\mu_i)-tq)(t_i-t)}{K_{2i}}+\frac{K_2\left(K_{2i}h_X\bar{X}-K_{1i}h_E(\mu-\mu_i)+h_Et_iZ_i+\left[sK_{1i}+\lambda^2t^2h_SK_{2i}\right]q\right)}{h_EK_{2i}}$.

The integral in the expression above is a multiple of a cumulative normal density, with mean $\left[\frac{A}{\frac{(t_i-t)^2}{K_{2i}}+\frac{K_{1i}(K_2)^2}{h_EK_{2i}}}\right]$ and variance $\frac{(t-t_i)^2}{K_{2i}}+\frac{K_{1i}(K_2)^2}{h_EK_{2i}}$. However, since this multiple is only a function of the variance, which is a constant that doesn't depend on m_1^i, we can ignore the whole integral for the analysis of optimal holdings at $t=1$.

Before we continue, we can further simplify $\frac{(t-t_i)^2}{K_{2i}}+\frac{K_{1i}(K_2)^2}{h_EK_{2i}}$ to:

$$
\begin{aligned}
\frac{(t_i-t)^2}{K_{2i}}+\frac{K_{1i}\left(K_2\right)^2}{h_EK_{2i}} &= \frac{1}{h_EK_{2i}}\left[h_E(t_i-t)^2+K_{1i}\left(K_2\right)^2\right] \\
&= K_{2i}-K_2+\frac{\left(K_2\right)^2-h_EK_2}{h_E}=(t_i-t)+\frac{K_1K_2}{h_E}. \quad \text{(A.10)}
\end{aligned}
$$

with $K_1\equiv\int K_{1i}di=h_X+t+\lambda^2t^2h_S$ and measures the average precision of beliefs about the liquidation value at $t=1$.

We can also show that A can be simplified to:

$$
A=\frac{K_2h_X\bar{X}}{h_E}+K_1\left(\mu_i-\mu\right)+t_iZ_i+\left[\frac{K_2\left(t+\lambda^2t^2h_S\right)}{h_E}-t\right]q.
$$

Thus, maximizing the objective function is equivalent to maximizing the exponent below:

$$
\underset{\left\{m_1^i\right\}}{\text{Max}}\left[\frac{1}{\lambda}m_1^iP_1+\frac{\left(-\frac{1}{\lambda}m_1^i+\frac{K_2h_X\bar{X}}{h_E}+K_1\left(\mu_i-\mu\right)+t_iZ_i+\left[\frac{K_2\left(t+\lambda^2t^2h_S\right)}{h_E}-t\right]q\right)^2}{2\left[(t_i-t)+\frac{K_1K_2}{h_E}\right]}\right].
$$

The first order conditions are:

$$\frac{P_1}{\lambda} = \frac{\frac{1}{\lambda}\left[-\frac{1}{\lambda}m_1^i + \frac{K_2 h_X \bar{X}}{h_E} + K_1(\mu_i - \mu) + t_i Z_i + \left(\frac{K_2\left(t+\lambda^2 t^2 h_S\right)}{h_E} - t\right)q\right]}{\left[(t_i - t) + \frac{K_1 K_2}{h_E}\right]},$$

$$\frac{m_1^i}{\lambda} = \frac{K_2 h_X \bar{X}}{h_E} + K_1(\mu_i - \mu) + t_i Z_i + \left(\frac{K_2\left(t+\lambda^2 t^2 h_S\right)}{h_E} - t\right)q - \left(t_i - t + \frac{K_1 K_2}{h_E}\right)P_1. \quad \text{(A.11)}$$

The market clearing condition implies that:

$$\frac{S}{\lambda} = \frac{K_2 h_X \bar{X}}{h_E} + K_1 \int (\mu_i - \mu)\, di + tX + \left(\frac{K_2\left(t+\lambda^2 t^2 h_S\right)}{h_E} - t\right)\left(X - \frac{S}{\lambda t}\right) - \frac{K_1 K_2}{h_E}P_1,$$

$$P_1 = \frac{1}{K_1}\left[h_X \bar{X} + \left(t + \lambda^2 t^2 h_S\right)X - \left(t + \lambda^2 t^2 h_S\right)\frac{S}{\lambda t}\right]. \quad \text{(A.12)}$$

Using the linear conjecture in equation (1) we match coefficients and obtain:

$$\phi_1 = 0,\ \alpha_1 = \frac{h_X}{K_1},\ \beta_1 = \frac{\left(t + \lambda^2 t^2 h_S\right)}{K_1},\ \gamma_1 = \frac{\left(\frac{1}{\lambda} + t\lambda h_S\right)}{K_1}. \quad \text{(A.13)}$$

We now return to equation (A.11) to compute demands at $t = 1$:

$$\frac{m_1^i}{\lambda} = \frac{K_2 h_X \bar{X}}{h_E} + \left[\frac{K_2 K_{1i} - h_E}{K_{2i}}\right](\mu_i - \mu) + t_i Z_i + \left(\frac{K_2\left(t+\lambda^2 t^2 h_S\right)}{h_E} - t\right)q - \left(t_i - t + \frac{K_1 K_2}{h_E}\right)P_1,$$

$$\frac{m_1^i}{\lambda} = t_i\varepsilon_i + \left[\frac{K_2 K_{1i} - h_E}{K_{2i}}\right](\mu_i - \mu) + \left(\frac{t_i - t}{K_1}\right)h_X\left(X - \bar{X}\right) + \left[tK_{1i} + (t_i - t)\left(\lambda^2 t^2 h_S\right)\right]\frac{S}{t\lambda K_1} - \frac{\left(t_i - t + \frac{K_1 K_2}{h_E}\right)}{K_1}\left[\frac{h_E}{K_2}\int\left(\frac{K_2 K_{1i} - h_E}{K_{2i}}\right)\frac{(\mu_i - \mu)}{K_1}di\right],$$

$$m_1^i = \lambda t_i \varepsilon_i + \lambda K_1(\mu_i - \mu) + \lambda\left(\frac{t_i - t}{K_1}\right)\left[h_X\left(X - \bar{X}\right) + \lambda t h_S S\right] + \left(\frac{K_{1i}}{K_1}\right)S. \quad \text{(A.14)}$$

Finally, to conclude the proof and show existence of equilibrium, it is easy to see that $\xi_1 = \frac{\gamma_1}{\beta_1} = \frac{1}{\lambda t} = \xi = \xi_2$. ■

Proof of Theorem 3. Change in holdings from $t = 0$ to $t = 1$ equals to:

$$m_1^i - m_0^i = \lambda\left[t_i\varepsilon_i + K_1\mu_i + \left(\frac{K_{1i}}{K_1}\right)\frac{S}{\lambda} + \frac{(t_i - t)}{K_1}\left[h_X\left(X - \bar{X}\right) + \lambda t h_S S\right]\right]. \quad \text{(A.15)}$$

The expected change in holdings before the announcement is:

$$E\left(m_1^i - m_0^i\right) = E\left(\lambda\left[t_i\varepsilon_i + K_1\mu_i + \frac{(t_i - t)}{K_1}\left[h_X\left(X - \bar{X}\right) + \lambda t h_S S\right] + \left(\frac{K_{1i}}{K_1}\right)\frac{S}{\lambda}\right]\right) = \lambda K_1 \mu_i. \quad \text{(A.16)}$$

The variance is given by:

$$Var\left(m_1^i - m_0^i\right) = \lambda^2 \left[t_i + \left(\frac{t_i - t}{K_1}\right)^2 h_X + \left(\frac{1}{K_1}\right)^2 \left(\frac{K_{1i}}{\lambda} + (t_i - t)\,\lambda t h_S\right)^2 \frac{1}{h_S}\right]. \quad \text{(A.17)}$$

The change in holdings around the announcement equals to:

$$\begin{aligned} m_2^i - m_1^i &= \lambda\left(-K_2\mu_i + \frac{(t_i - t)\,h_E}{K_1 K_2}\left[h_X\left(\bar{X} - X\right) - \left(\frac{1}{\lambda} + \lambda t h_S\right) S + K_1\left(v - \mu\right)\right]\right) \\ &= \lambda\left[-K_2\mu_i - (t_i - t)\left(P_2 - P_1\right)\right]. \qquad \text{(A.18)} \end{aligned}$$

Before we compute the mean and variance, note that we can characterize price change and its moments by:

$$P_2 - P_1 = \left(\frac{h_E}{K_2}\right)\left[E - P_1\right], \quad \text{(A.19)}$$

$$E\left(P_2 - P_1\right) = \frac{h_E}{K_2}\left[\bar{X} - \bar{X}\right] = 0, \quad \text{(A.20)}$$

$$Var\left(P_2 - P_1\right) = \left(\frac{h_E}{K_2}\right)^2 \left[\begin{array}{c} \frac{1}{h_E} + \frac{1}{h_X} - \frac{2t\left(1+\lambda^2 t h_S\right)}{K_1 h_X} \\ + \left(\frac{1+\lambda^2 t h_S}{K_1}\right)^2 \left(\frac{t^2}{h_X} + \frac{1}{h_S \lambda^2}\right) \end{array}\right]. \quad \text{(A.21)}$$

Using these results we have:

$$\begin{aligned} E\left(m_2^i - m_1^i\right) &= \lambda\left[-K_2\mu_i - (t_i - t)\,E\left(P_2 - P_1\right)\right] \qquad \text{(A.22)} \\ &= \lambda\left[-K_2\mu_i - (t_i - t)\,\frac{h_E}{K_2}\left[\bar{X} - \bar{X}\right]\right] \\ &= -\lambda K_2 \mu_i. \qquad \text{(A.23)} \end{aligned}$$

and

$$\begin{aligned} Var\left(m_2^i - m_1^i\right) &= Var\left(\lambda\left[-K_2\mu_i - (t_i - t)\left(P_2 - P_1\right)\right]\right) \qquad \text{(A.24)} \\ &= \lambda^2 (t_i - t)^2\, Var\left(P_2 - P_1\right) \\ &= \lambda^2 (t_i - t)^2 \left(\frac{h_E}{K_2}\right)^2 \left[Var(E) + Var(P_1) - 2Cov\left(E, P_1\right)\right] \\ &= \lambda^2 (t_i - t)^2 \left(\frac{h_E}{K_2}\right)^2 \left[\begin{array}{c} \frac{1}{h_E} + \frac{1}{h_X} - \frac{2t h_X\left(1+\lambda^2 t h_S\right)}{K_1} \\ + \left(\frac{1+\lambda^2 t h_S}{K_1}\right)^2 \left(\frac{t^2}{h_X} + \frac{1}{h_S \lambda^2}\right) \end{array}\right]. \qquad \text{(A.25)} \end{aligned}$$

■

Proof of Theorem 4. The derivative of trading volume before announcements with respect to belief μ_i is:

$$\left.\frac{\partial E\left(Vol_1^i\right)}{\partial \mu_i}\right|_{\mu=0} = \left.\frac{\partial 2\sigma_1^i n\left(\frac{\mu_1^i}{\sigma_1^i}\right) - \mu_1^i\left[1-2\Phi\left(\frac{\mu_1^i}{\sigma_1^i}\right)\right]}{\partial \mu_i}\right|_{\mu=0} \tag{A.26}$$

$$= -2\left(\frac{\mu_1^i}{\sigma_1^i}\right) n\left(\frac{\mu_1^i}{\sigma_1^i}\right) * \lambda K_1 - \left[1-2\Phi\left(\frac{\mu_1^i}{\sigma_1^i}\right)\right]\lambda K_1$$
$$+2\left(\frac{\mu_1^i}{\sigma_1^i}\right)\left[n\left(\frac{\mu_1^i}{\sigma_1^i}\right)\right]\lambda K_1 \tag{A.27}$$

$$= -2\lambda K_1\left[\frac{1}{2} - \Phi\left(\frac{\lambda K_1 \mu_i}{\sigma_1^i}\right)\right] > 0 \Longleftrightarrow \mu_i > 0. \tag{A.28}$$

Now for the derivative of expected trading volume before announcements with respect to the precision of public signals:

$$\left.\frac{\partial E\left(Vol_1^i\right)}{\partial t_i}\right|_{fixed\, t} = \left[2n\left(\frac{\mu_1^i}{\sigma_1^i}\right) + 2\left(\frac{\mu_1^i}{\sigma_1^i}\right)^2 n\left(\frac{\mu_1^i}{\sigma_1^i}\right) - 2n\left(\frac{\mu_1^i}{\sigma_1^i}\right)\right] * \left.\frac{\partial \sigma_1^i}{\partial t_i}\right|_{fixed\, t}$$
$$= 2n\left(\frac{\mu_1^i}{\sigma_1^i}\right) * \left.\frac{\partial \sigma_1^i}{\partial t_i}\right|_{fixed\, t}.$$

The sign of the derivative above depends on how the standard deviation of the change in holdings, $m_1^i - m_0^i$, varies with t_i. Below, I show that it is positive for all positive values of t_i, concluding the proof:

$$\left.\frac{\partial \sigma_1^i}{\partial t_i}\right|_{fixed\, t} = \frac{\partial \lambda\left[t_i + \left(\frac{t_i - t}{K_1}\right)^2 h_X + \left(\frac{1}{K_1}\right)^2\left(\frac{K_{1i}}{\lambda} + (t_i - t)\lambda t h_S\right)^2 \frac{1}{h_S}\right]^{\frac{1}{2}}}{\partial t_i} \tag{A.29}$$

$$= \frac{\lambda^2}{2\sigma_1^i} * \left[1 + 2\left(\frac{t_i - t}{K_1}\right)\frac{h_X}{K_1} + \frac{2}{(K_1)^2}\left(\frac{1+\lambda^2 t h_S}{\lambda^2 h_S}\right)\left[h_X + t_i + \lambda^2 t t_i h_S\right]\right]$$

$$= \frac{\lambda^2}{2\sigma_1^i}\left\{1 + \frac{2t_i h_X}{(K_1)^2} + \frac{2}{(K_1)^2}\left[\begin{array}{c}\left(\frac{h_X + t_i + \lambda^2 t t_i h_S}{\lambda^2 h_S}\right) \\ +t * t_i\left(1+\lambda^2 t h_S\right)\end{array}\right]\right\} \tag{A.30}$$

$$> 0 \text{ for all } t_i > 0.$$

For trading around announcements, we use equation (A.26) to show that:

$$\begin{aligned}
\left.\frac{\partial E\left(Vol_2^i\right)}{\partial \mu_i}\right|_{\mu=0} &= \left.\frac{\partial 2\sigma_2^i n\left(\frac{\mu_2^i}{\sigma_2^i}\right) - \mu_2^i\left[1-2\Phi\left(\frac{\mu_2^i}{\sigma_2^i}\right)\right]}{\partial \mu_i}\right|_{\mu=0} \\
&= 2\lambda K_2\left[\frac{1}{2} - \Phi\left(\frac{-\lambda K_2 \mu_i}{\sigma_2^i}\right)\right] \\
&= 2\lambda K_2\left[\frac{1}{2} - \left[1 - \Phi\left(\frac{\lambda K_2 \mu_i}{\sigma_2^i}\right)\right]\right] && \text{(A.31)} \\
&= -2\lambda K_2\left[\frac{1}{2} - \Phi\left(\frac{\lambda K_2 \mu_i}{\sigma_2^i}\right)\right] > 0 \Longleftrightarrow \mu_i > 0. && \text{(A.32)}
\end{aligned}$$

Finally, the derivative with respect to t_i is:

$$\begin{aligned}
\left.\frac{\partial E\left(Vol_2^i\right)}{\partial t_i}\right|_{fixed\, t} &= \left[2n\left(\frac{\mu_2^i}{\sigma_2^i}\right) + 2\left(\frac{\mu_2^i}{\sigma_2^i}\right)^2 n\left(\frac{\mu_2^i}{\sigma_2^i}\right) - 2n\left(\frac{\mu_2^i}{\sigma_2^i}\right)^2\right] * \left.\frac{\partial \sigma_2^i}{\partial t_i}\right|_{fixed\, t} \\
&= 2\lambda n\left(\frac{\mu_2^i}{\sigma_2^i}\right)\sqrt{Var\left(P_2 - P_1\right)} > 0 \text{ for all } t_i > 0. && \text{(A.33)}
\end{aligned}$$

■

Proof of Theorem 5. An increase in dispersion that keeps fixed the average belief μ is such that:

$$\begin{aligned}
d\mu &= \gamma d\mu_I + (1-\gamma)\, d\mu_U = 0 \\
&\Rightarrow \; d\mu_I = -\frac{(1-\gamma)}{\gamma} d\mu_U. && \text{(A.34)}
\end{aligned}$$

Combining equations (23) and (A.34), the total differential of aggregate expected volume before announcements given a mean-preserving spread with respect to dispersion is given by:

$$\begin{aligned}
dE\left(Vol_1^{Tot}\right) &= \gamma * \left(\frac{\partial E\left(Vol_1^I\right)}{\partial \mu_I}\right) d\mu_I + (1-\gamma) * \left(\frac{\partial E\left(Vol_1^U\right)}{\partial \mu_U}\right) d\mu_U, \\
\frac{dE\left(Vol_1^{Tot}\right)}{d\mu_U} &= 2(1-\gamma)\lambda K_1\left[\Phi\left(\lambda K_1 \frac{\mu_U}{\sigma_1^U}\right) - \Phi\left(\lambda K_1 \frac{\mu_I}{\sigma_1^I}\right)\right] > 0 \Leftrightarrow \mu_U > \mu_I && \text{(A.35)}
\end{aligned}$$

For expected volume after an announcement we combine (25) and (A.34) to obtain:

$$\begin{aligned}
dE\left(Vol_2^{Tot}\right) &= \gamma * \left(\frac{\partial E\left(Vol_2^I\right)}{\partial \mu_I}\right) d\mu_I + (1-\gamma) * \left(\frac{\partial E\left(Vol_2^U\right)}{\partial \mu_U}\right) d\mu_U, \\
\frac{dE\left(Vol_2^{Tot}\right)}{d\mu_U} &= 2(1-\gamma)\lambda K_2\left[\Phi\left(\lambda K_2 \frac{\mu_U}{\sigma_2^U}\right) - \Phi\left(\lambda K_2 \frac{\mu_I}{\sigma_2^I}\right)\right] > 0 \Leftrightarrow \mu_U > \mu_I && \text{(A.36)}
\end{aligned}$$

The proof for the derivative with respect to information asymmetry is computed in similar fashion. An increase in t_U such average precision t is constant is given by:

$$\begin{aligned} dt &= \gamma dt_I + (1-\gamma) dt_U = 0 \\ &\Rightarrow dt_I = -\frac{(1-\gamma)}{\gamma} dt_U. \end{aligned}$$

Given an increase in t_U, the total differential of aggregate expected volume after an announcement is:

$$\begin{aligned} dE\left(Vol_2^{Tot}\right) &= \gamma * \left(\frac{\partial E\left(Vol_2^I\right)}{\partial t_I}\right) dt_I + (1-\gamma) * \left(\frac{\partial E\left(Vol_2^U\right)}{\partial t_U}\right) dt_U, \\ \frac{dE\left(Vol_2^{Tot}\right)}{dt_U} &= -\gamma 2\lambda n\left(\frac{-\lambda K_2 \mu_I}{\sigma_2^I}\right)\sqrt{Var\left(P_2-P_1\right)}\frac{(1-\gamma)}{\gamma} dt_U + \\ &\quad (1-\gamma) 2\lambda n\left(\frac{-\lambda K_2 \mu_U}{\sigma_2^U}\right)\sqrt{Var\left(P_2-P_1\right)} dt_U, \qquad \text{(A.37)} \\ \frac{dE\left(Vol_2^{Tot}\right)}{dt_U} &= 2(1-\gamma)\lambda\sqrt{Var\left(P_2-P_1\right)}\left[n\left(\frac{-\lambda K_2 \mu_U}{\sigma_2^U}\right) - n\left(\frac{-\lambda K_2 \mu_I}{\sigma_2^I}\right)\right] \\ &= 2(1-\gamma)\lambda\sqrt{Var\left(P_2-P_1\right)}\left[n\left(\frac{\lambda K_2 \mu_U}{\sigma_2^U}\right) - n\left(\frac{\lambda K_2 \mu_I}{\sigma_2^I}\right)\right] \qquad \text{(A.38)} \\ &> 0 \Leftrightarrow n\left(\frac{\lambda K_2 \mu_U}{\sigma_2^U}\right) > n\left(\frac{\lambda K_2 \mu_I}{\sigma_2^I}\right) \Leftrightarrow \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\lambda K_2 \mu_U}{\sigma_2^U}\right)^2} > \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\lambda K_2 \mu_I}{\sigma_2^I}\right)^2} \\ &\Leftrightarrow \left(\frac{\mu_U}{\sigma_2^U}\right)^2 < \left(\frac{\mu_I}{\sigma_2^I}\right)^2. \end{aligned}$$

But note that since $\sigma_2^U > \sigma_2^I$, it is sufficient to check whether $(\mu_U)^2 < (\mu_I)^2$. Since $\mu = 0$, $\mu_I = -\left(\frac{1-\gamma}{\gamma}\right)\mu_U$ and we have:

$$\begin{aligned} (\mu_U)^2 &< (\mu_I)^2 \Leftrightarrow (\mu_U)^2 < \left(\frac{1-\gamma}{\gamma}\right)^2 (\mu_U)^2 \\ &\Leftrightarrow 1 < \left(\frac{1-\gamma}{\gamma}\right)^2 = \left(\frac{1}{\gamma}-1\right)^2. \end{aligned}$$

■

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Table 1: Descriptive Statistics

This table reports descriptive statistics of annual earnings announcements in the 1984–2002 period on I/B/E/S with available PIN estimates. Panel A lists firm characteristics, Panel B their correlations and Panel C statistics of turnover measures. PIN represents the probability of information-based trading, Dispersion is the standard deviation of analyst forecasts as a percentage of share price, Size reports statistics for average market capitalization in millions of dollars and Analysts represents analyst coverage. E(r) is the average percentage daily returns, $\sigma(r)$ their standard deviation and Turnover daily percentage turnover during the period between $t = -80$ and $t = -11$ days before the event. In Panel B, Coverage uses residual analyst coverage when computing correlations. In Panel C, I report statistics for Turnover transformed with the log(0.001+x) function. Before represents abnormal trading during the [-10,-3] days period before the announcement, Around stands for the [-2,2] days period around the announcement and Difference is equal to (Around–Before).

Panel A: Explanatory Variables

Statistic	PIN	Dispersion	Size	Analysts	$E(r)$	$\sigma(r)$	Turnover
Mean	0.171	0.56	3,441	12.25	0.085	2.473	0.341
Median	0.166	0.21	959	10.00	0.088	2.137	0.262
St. Dev.	0.055	1.22	9,832	8.19	0.337	1.385	0.294
Skewness	0.66	5.13	10.10	1.00	0.21	3.04	3.38
Kurtosis	3.93	32.61	167.50	3.47	13.21	25.84	22.71
Min	0.000	0.00	6	3.00	-2.749	0.321	0.044
Max	0.551	9.05	308,939	50.00	6.279	30.534	3.501

Panel B: Correlations

Corr(↓,→)	PIN	Dispersion	Size	Analysts	$E(r)$	$\sigma(r)$	Turnover
PIN	1						
Dispersion	0.162	1					
Size	-0.328	-0.100	1				
Analysts	-0.411	-0.086	0.417	1			
$E(r)$	0.004	-0.059	0.016	-0.025	1		
$\sigma(r)$	0.119	0.417	-0.099	-0.222	0.007	1	
Turnover	-0.103	0.054	-0.022	0.045	0.010	0.408	1

Panel C: Log turnover Measures

Variable	N	Mean	Median	St. Dev.	Skewness	Kurtosis	Min	Max
Estimation	20,403	-1.643	-1.604	0.802	-0.293	3.484	-4.034	1.028
Before	20,403	-1.616	-1.580	0.899	-0.337	3.652	-5.440	1.541
Around	20,403	-1.370	-1.346	0.938	-0.232	3.441	-5.269	2.073
Difference	20,403	0.245	0.215	0.549	0.338	4.509	-2.753	3.739

Table 2: Turnover Before Earnings Announcements

This table reports results of OLS regressions of turnover before earnings announcements events taken from I/B/E/S in the 1984–2002 period. The dependent variable is average log turnover on the [-10,-3] days period before the announcement. Under the Sign column I show the predicted signs for each variable. D_{PIN} is a dummy variable equal to one if the firm has a PIN estimate for the previous year. PIN is the probability of informed-based trading computed by Easley, Hvidkjaer, and O'Hara (2002), dispersion is analysts' forecast dispersion, $|Ret|$ is the average absolute return during the estimation period, $|Ret_{Mkt}|$ the market's mean absolute return, Ln(Size) is the log of average market capitalization, Analysts is the number of analysts covering the stock and $\mu(ret)$ the estimation-period average return. P-values reported between brackets controls for heteroscedasticity using Froot (1989)'s adjustment and clustered at the firm level.

Variable	Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\|Ret\|$	+					15.295	15.403	15.336	11.032
						[0.00]	[0.00]	[0.00]	[0.00]
$\|Ret_{Mkt}\|$	+					11.338	9.546	9.592	10.562
						[0.00]	[0.00]	[0.00]	[0.00]
D_{PIN}	+								-0.637
									[0.00]
PIN	-	-5.171		-5.324	-4.184	-4.030	-2.045	-1.808	
		[0.00]		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	
Dispersion	+		0.387	4.282	6.121	7.635	8.599	17.186	6.064
			[0.64]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Disp*PIN	-							-42.618	
								[0.00]	
Ln(Size)	+						-0.008	-0.006	0.062
							[0.55]	[0.67]	[0.00]
Analysts (÷100)	+						2.667	2.662	3.321
							[0.00]	[0.00]	[0.00]
Constant	?	-0.731	-1.618	-0.728	-0.180	-1.282	-1.963	-2.028	-2.350
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Obs.		20,403	20,403	20,403	20,403	19,945	19,945	19,945	43,307
R^2		10.04%	0.00%	10.36%	16.02%	18.16%	22.11%	22.17%	23.91%
N$^{o.}$ of firms		2,730	2,730	2,730	2,730	2,704	2,704	2,704	7,195
Year Dummies		No	No	No	Yes	Yes	Yes	Yes	Yes

Table 3: Turnover Around Earnings Announcements

This table reports results of OLS regressions of turnover around earnings announcements events taken from I/B/E/S in the 1984–2002 period. The dependent variable is the average log turnover on the [-2,+2] days period around announcements. Under the Sign column I show the predicted signs for each variable. D_{PIN} is a dummy variable equal to one if the firm has a PIN estimate for the previous year. PIN is the probability of informed-based trading computed by Easley, Hvidkjaer, and O'Hara (2002), dispersion is analysts' forecast dispersion, $|Ret|$ is the average absolute return during the estimation period, $|Ret_{Mkt}|$ the market's mean absolute return, Ln(Size) is the log of average market capitalization, Analysts is the number of analysts covering the stock and $\mu(ret)$ the estimation-period average return. P-values reported between brackets controls for heteroscedasticity using Froot (1989)'s adjustment and clustered at the firm level.

Variable	Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\|Ret\|$	+					18.973	19.028	19.005	16.209
						[0.00]	[0.00]	[0.00]	[0.00]
$\|Ret_{Mkt}\|$	+					2.947	2.511	2.504	2.707
						[0.11]	[0.16]	[0.16]	[0.06]
D_{PIN}	+								-0.662
									[0.00]
PIN	-	-4.474		-4.591	-3.345	-3.391	-1.681	-1.397	
		[0.00]		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	
Dispersion	+		-0.096	3.263	5.588	6.060	6.715	16.984	3.539
			[0.90]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Disp*PIN	-							-50.986	
								[0.00]	
Ln(Size)	+						-0.019	-0.016	0.040
							[0.18]	[0.26]	[0.00]
Analysts (÷100)	+						2.540	2.534	3.254
							[0.00]	[0.00]	[0.00]
Constant	?	-0.605	-1.370	-0.603	0.034	-1.335	-1.875	-1.953	-0.768
		[0.00]	[0.00]	[0.00]	[0.57]	[0.00]	[0.00]	[0.00]	[0.00]
Obs.		20,403	20,403	20,403	20,403	19,937	19,937	19,937	43,285
R^2		6.90%	-0.01%	7.07%	13.29%	19.74%	22.71%	22.80%	27.00%
N$^{o.}$ of firms		2,730	2,730	2,730	2,730	2,704	2,704	2,704	7,194
Year Dummies		No	No	No	Yes	Yes	Yes	Yes	Yes

Table 4: Difference between Turnover Around and Turnover Before Announcements

This table reports OLS regression results of turnover difference between the periods around and before earnings announcements events taken from I/B/E/S in the 1984–2002 period for which there are PIN estimates available. The dependent variable is the difference in average daily log turnover before and around an earnings announcement. Trading before comprises average turnover for the [-10,-3] period before announcements and trading around uses turnover for the [-2,2] period around announcements. Under the Sign column I show the predicted signs for each variable. D_{PIN} is a dummy variable equal to one if the firm has a PIN estimate for the previous year. PIN is the probability of informed-based trading computed by Easley, Hvidkjaer, and O'Hara (2002), dispersion is analysts' forecast dispersion, $|Ret|$ is the average absolute return during the estimation period, $|Ret_{Mkt}|$ the market's mean absolute return, Ln(Size) is the log of average market capitalization, Analysts is the number of analysts covering the stock and $\mu(ret)$ the estimation-period average return. P-values reported between brackets controls for heteroscedasticity using Froot (1989)'s adjustment and clustered at the firm level.

Variable	Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\|Ret\|$	+					15.357	15.330	15.332	12.489
						[0.00]	[0.00]	[0.00]	[0.00]
$\|Ret_{Mkt}\|$	+					10.562	10.286	10.279	9.345
						[0.00]	[0.00]	[0.00]	[0.00]
D_{PIN}	-								-0.030
									[0.00]
PIN	+	0.700		0.735	0.839	0.661	0.368	0.419	
		[0.00]		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	
Dispersion	+		-0.446	-0.984	-0.510	-1.345	-1.705	0.155	-2.445
			[0.21]	[0.01]	[0.17]	[0.00]	[0.00]	[0.93]	[0.00]
Disp*PIN	-							-9.239	
								[0.32]	
Ln(Size)	-						-0.013	-0.012	-0.024
							[0.01]	[0.01]	[0.00]
Analysts (÷100)	-						-0.108	-0.109	-0.036
							[0.12]	[0.12]	[0.52]
Constant	?	0.125	0.247	0.124	0.213	-0.062	0.093	0.079	0.306
		[0.00]	[0.00]	[0.00]	[0.00]	[0.02]	[0.04]	[0.09]	[0.00]
Obs.		20,403	20,403	20,403	20,403	19,937	19,937	19,937	43,282
R^2		0.49%	0.01%	0.53%	1.47%	17.47%	17.60%	17.61%	15.11%
N$^{o.}$ of firms		2,730	2,730	2,730	2,730	2,704	2,704	2,704	7,193
Year Dummies		No	No	No	Yes	Yes	Yes	Yes	Yes

Table 5: Estimated Impact on Stock Turnover

This table contains estimated changes in abnormal turnover measures given one standard deviation increases from the mean for PIN, analyst forecast dispersion and analyst coverage. Panel A contains results for turnover before announcements, Panel B uses turnover around announcements and Panel C the changes on the difference between average turnover after and before events. The sample is comprised by earnings announcements events from I/B/E/S in the 1984–2002 period for which there are PIN estimates available. Under column β, I list the parameters in column 6 from tables 2, 3 and 4 for each respective variable, μ displays means and σ standard deviations. $\Delta(\sigma)$ shows change in terms of dependent variables' standard deviations, while $\Delta(\%)$ changes in terms of percentage changes with respect to the average of the dependent variable. LB and UB represent 95% lower and upper confidence intervals.

Panel A: Turnover Before

Variable	β	μ	σ	$\Delta(\sigma)$	$\Delta(\%)$	LB: $\Delta(\%)$	UB: $\Delta(\%)$
PIN	-2.045	0.171	0.055	-0.125	-6.98%	-8.59%	-5.36%
Dispersion	8.599	0.006	0.012	0.117	6.49%	5.31%	7.67%
Analysts	2.667	12.255	10.000	0.297	16.51%	13.72%	0.41%

Panel B: Turnover Around

Variable	β	μ	σ	$\Delta(\sigma)$	$\Delta(\%)$	LB: $\Delta(\%)$	UB: $\Delta(\%)$
PIN	-1.681	0.171	0.055	-0.099	-6.76%	-8.70%	-4.82%
Dispersion	6.715	0.006	0.012	0.087	5.98%	4.53%	7.42%
Analysts	2.540	12.255	10.000	0.271	18.54%	15.12%	0.41%

Panel C: Turnover Difference

Variable	β	μ	σ	$\Delta(\sigma)$	$\Delta(\%)$	LB: $\Delta(\%)$	UB: $\Delta(\%)$
PIN	0.368	0.171	0.055	0.037	8.29%	4.08%	12.50%
Dispersion	-1.705	0.006	0.012	-0.038	-8.50%	-12.18%	-4.83%
Analysts	-0.108	12.255	10.000	-0.020	-4.40%	-10.00%	0.02%

Table 6: Testing for sample-selection bias due to PIN availability

Panel A reports statistics of firms with and without PIN estimates, using CRSP and I/B/E/S earnings announcements data between 1983-2002. The third column tests whether means are statistically significant. An '*' denotes significance at the 1% level. In Panel B, I report regression results based on the Heckman (1979) two-step model to account for sample-selection. The probit equation uses PIN-availability as the dependent variable. Age is based on the first year of stock data availability in CRSP, Dispersion is analysts' forecast dispersion, Analysts is the number of analysts covering the stock, Inst. Ownership is the fraction of the firm owned by institutional investors based on 13f Holdings data, Number of Inst. is the number of institutional investors owners, Ln(Size) is the log of average market capitalization and $\sigma(ret)$ the standard deviation of return during the 200-day estimation period. Specification under "Heckman model" use stock turnover measures as dependent variables and the inverse-Mills ratio (λ) is computed from the first-step probit model. P-values are reported between brackets.

Panel A: Differences between no-PIN and PIN firms

	No-PIN sample			PIN sample			Difference in means
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	No-PIN minus PIN
Before	18,936	-1.17	1.26	19,690	-1.62	0.90	0.45*
Around	18,938	-0.82	1.30	19,690	-1.37	0.93	0.55*
Diff	18,936	0.35	0.74	19,690	0.25	0.55	0.10*
Dispersion	18,938	0.59	1.30	19,690	0.56	0.01	0.04*
Size	18,938	1,626	13,355	19,690	3,448	9,739	-1822*

Panel B: Heckman two-step model

Probit Model		Heckman Model			
Dependent Variable	D_{PIN}		Before	Around	Diff
Dispersion	13.644	$\|Ret\|$	15.647	18.894	15.269
	[0.00]		[0.00]	[0.00]	[0.00]
Ln(Size)	0.163	$\|Ret_{Mkt}\|$	10.053	2.539	10.228
	[0.00]		[0.00]	[0.19]	[0.00]
Analysts (÷100)	1.762	PIN	-2.190	-1.862	0.327
	[0.00]		[0.00]	[0.00]	[0.00]
Age	0.027	Dispersion	9.089	7.267	-1.635
	[0.00]		[0.00]	[0.00]	[0.00]
Inst. Ownership	0.479	Ln(Size)	0.004	-0.004	-0.009
	[0.00]		[0.61]	[0.57]	[0.03]
Number of Inst. Investors	-0.003	Analysts (÷100)	2.652	2.522	-0.111
	[0.00]		[0.00]	[0.00]	[0.12]
$\sigma(ret)$	-16.891	Constant	-1.896	-1.719	0.196
	[0.00]		[0.00]	[0.00]	[0.00]
Market Turnover	1.867	λ	0.174	0.216	0.048
	[0.00]		[0.00]	[0.00]	[0.00]
Nasdaq-listing	-2.773				
	[0.00]				
Constant	-0.888				
	[0.00]				
Obs.	38,093		38,101	38,093	38,093
Pseudo R2	63.42%	Adjusted R2	21.98%	21.61%	17.60%
Year FE	Yes		Yes	Yes	Yes

Table 7: Robustness Checks - Quarterly data and Alternative Event Window

This table regress turnover measures on proxies for differences of opinion and information asymmetry, using earnings announcements data taken from I/B/E/S in the 1984–2002 period for which there are PIN estimates available. Panel A reports results using quarterly data, where "Before" uses turnover for the [-10,-3] period before announcements. "Around" uses the [-2,2] period around the event and "Diff" equals Around-Before. In Panel B, I change the calculation of dependent variables and define "Before" as turnover for the [-10,-2] period before announcements and "Around" as [-1,1] days-period around the event. PIN is the probability of informed-based trading computed by Easley, Hvidkjaer, and O'Hara (2002), dispersion is analysts' forecast dispersion, $|Ret|$ is the average absolute return during the estimation period, $|Ret_{Mkt}|$ the market's mean absolute return, Ln(Size) is the log of average market capitalization, Analysts is the number of analysts covering the stock and $\mu(ret)$ the estimation-period average return. P-values reported between brackets in Panel A controls for heteroscedasticity using Froot (1989)'s adjustment and clustered at the firm level. In Panel B they are based on 500 bootstrap replications.

	Panel A: Quarterly Data			Panel B: [-1,1] "Around" window		
Variable	Before	Around	Diff	Before	Around	Diff
$\|Ret\|$	11.941	17.024	15.482	15.578	16.504	13.369
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
$\|Ret_{Mkt}\|$	8.642	3.242	8.102	9.466	3.002	9.557
	[0.00]	[0.00]	[0.00]	[0.00]	[0.09]	[0.00]
PIN	-1.511	-1.225	0.269	-2.037	-1.548	0.487
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Dispersion	22.155	18.748	-3.159	8.624	6.157	-2.189
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Ln(Size)	-0.030	-0.053	-0.025	-0.008	-0.026	-0.020
	[0.01]	[0.00]	[0.00]	[0.55]	[0.07]	[0.00]
Analysts ($\div$100)	4.668	4.950	0.322	2.657	2.568	-0.050
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.52]
Constant	-1.699	-1.323	0.273	-1.961	-0.374	0.387
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Obs.	64,626	64,605	64,604	19,945	19,857	19,857
R^2	22.06%	24.01%	18.02%	21.93%	22.69%	17.75%
N$^{o.}$ of firms	2,589	2,589	2,589	2,704	2,701	2,701
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Robustness Checks - Split Sample

This table regress turnover measures on proxies for differences of opinion and information asymmetry, using annual earnings announcements data taken from I/B/E/S in the 1984–2002 period for which there are PIN estimates available. Panel A shows results for the 1984-1993 period, while Panel B uses data from 1994-2002. “Before” uses turnover for the [-10,-3] period before announcements in excess of mean turnover calculated for the estimation-period. “Around” uses the [-2,2] period around the event and “Diff” equals Around-Before. PIN is the probability of informed-based trading computed by Easley, Hvidkjaer, and O’Hara (2002), dispersion is analysts’ forecast dispersion, $|Ret|$ is the average absolute return during the estimation period, $|Ret_{Mkt}|$ the market’s mean absolute return, Ln(Size) is the log of average market capitalization, Analysts is the number of analysts covering the stock and $\mu(ret)$ the estimation-period average return. P-values reported between brackets controls for heteroscedasticity using Froot (1989)’s adjustment and clustered at the firm level.

	Panel A: 1984-1993			Panel B: 1994-2002		
Variable	Before	Around	Diff	Before	Around	Diff
$\|Ret\|$	17.884	20.115	18.353	14.003	18.433	13.763
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
$\|Ret_{Mkt}\|$	16.283	6.852	16.118	1.762	-1.607	5.580
	[0.00]	[0.00]	[0.00]	[0.54]	[0.57]	[0.00]
PIN	-2.048	-1.854	0.206	-2.029	-1.523	0.508
	[0.00]	[0.00]	[0.17]	[0.00]	[0.00]	[0.00]
Dispersion	9.071	7.785	-1.207	6.201	2.489	-3.371
	[0.00]	[0.00]	[0.00]	[0.00]	[0.12]	[0.00]
Ln(Size)	-0.039	-0.048	-0.012	0.004	-0.010	-0.016
	[0.04]	[0.02]	[0.14]	[0.78]	[0.52]	[0.01]
Analysts ($\div$100)	2.752	2.565	-0.165	2.889	2.828	-0.027
	[0.00]	[0.00]	[0.12]	[0.00]	[0.00]	[0.77]
Constant	-1.776	-1.669	0.106	-0.811	-0.863	0.238
	[0.00]	[0.00]	[0.11]	[0.00]	[0.00]	[0.00]
Obs.	9,420	9,413	9,413	10,525	10,524	10,524
R^2	16.10%	15.70%	17.36%	21.48%	22.46%	18.67%
$N^{o.}$ of firms	1,649	1,649	1,649	2,326	2,326	2,326
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

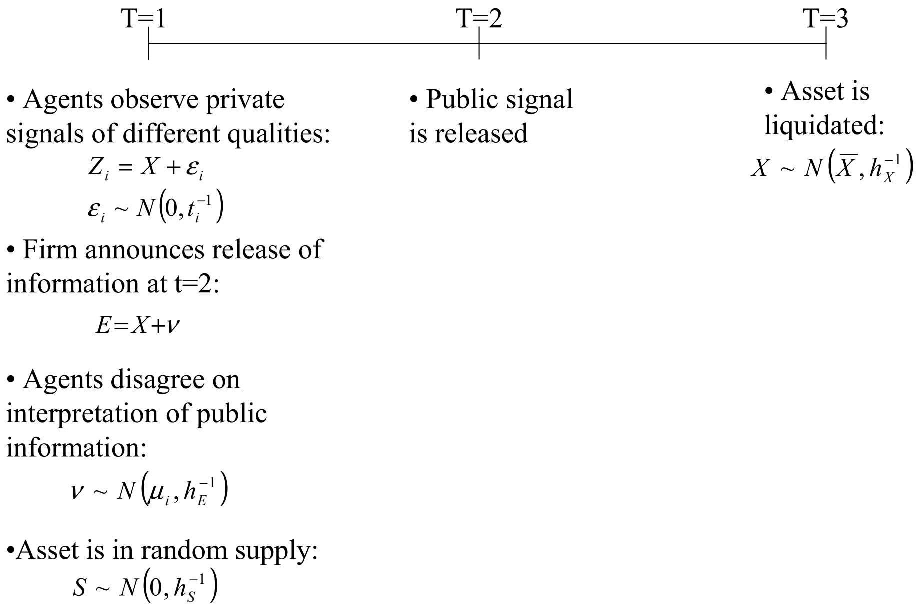

Figure 1: A summary of the time line of events in the model.

Figure 2: Abnormal Stock Turnover around Earnings Announcements

This graph shows abnormal turnover of earnings announcements events in the 1984–2002 period from the I/B/E/S database. Abnormal turnover is defined as the difference between daily turnover and the estimation-period average. The estimation-period comprises t=-80 to t=-11 days before the event. Turnover measures are winsorized at the 1% level. The sample is split between firms with and without estimates for the probability of information-based trading (PIN).