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# Determinants of Intra-Day Stock Price Change and Asymmetric Information\*

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## Abstract

This paper presents a synthesized model of asymmetric information. An empirical analysis of more than 1,400 NYSE common stocks shows that trade direction is more important than volume in revealing the asymmetry. There is also evidence to suggest that signed duration reflects informed trading activity. We use the proposed measure of information asymmetry to study daily changes in the level of informed trading and find that earnings announcements narrow the information gap between the informed and the uninformed. On average, information asymmetry is largest at the beginning of the trading day and it decreases monotonically toward the closing bell. More importantly, the asymmetric information measure is negatively related to the number of shareholders, number of analysts following a firm and whether there is an exchange-traded equity option written on the firm's stock. An implication of this finding is that firms can reduce information asymmetry by implementing disclosure measures that attract not only more investors and analysts but also option writers.

Keywords: Market Microstructure, Information Asymmetry

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The information structure of a firm is determined largely by the information channels through which the state of the firm is revealed to the world. For listed firms, the primary channel is the stock market. Through the stock market, traders convey and exchange information. Better informed traders convey more information, and stand a better chance of making a profit in the market. Before the release of material information, those who know it and transact ahead of public disclosure are privately informed traders. Investors who do not know the private information is referred to as uninformed traders. In particular, market makers are also uninformed and they trade in a way that minimizes their losses to insiders. Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985) and many others draw a crisp line between those who have private information and those who do not.

This definition is somewhat narrow and inadequate for two reasons. Firstly, trading on material information before public announcement is illegal in many countries and certainly in the U.S. where insider trading laws are enforced. In the absence of evidence to the contrary, it is reasonable to believe that most insiders are law-abiding with respect to these laws. Nonetheless, Easley, Hvidkjaer, and O'Hara (2002) find that the probability of informed trading (PIN) is 19.1% on average for NYSE-listed firms. Namely, in 19 out of 100 trading days, informed investors are trading with private information. If informed traders were all insiders, it would appear that despite the laws, insider trading is quite rampant and unchecked in the U.S. market. It would also imply that law enforcement agencies such as the SEC were not doing enough to curtail illegal insider trading.

Secondly, in markets populated by professional dealers only, adverse selection costs are still significant. An example is the inter-dealer Treasury market analyzed by Green (2004). Intriguingly, Green finds that the level of information asymmetry as measured by a modified model of Madhavan, Richardson, and Roomans (1997) increases *after* the scheduled release of macroeconomic data. How could information asymmetry prevail among these professional traders with regard to *public* information?

Of course, one can turn the empirical evidence around to suggest that the structural PIN model and the measure used by Green are misspecified. As a matter of fact, all empirical analyses can only *infer* the existence of asymmetric information from the data, as these data do not provide any indicator as to which orders and trades are motivated by private information. It could well be that the models are prone to infer that there is information asymmetry even when privately informed traders are not trading. Several papers document evidence that casts doubts on existing econometric models of information asymmetry. For example, Neal and Wheatley (1998) conclude that the adverse selection components of closed-end funds are larger than expected. They suspect that some

of the popular models of asymmetric information might be misspecified. Van Ness, Van Ness, and Warr (2001) also ascertain that existing measures of adverse selection costs relate inconsistently to the corporate finance proxies for the information structure of a firm.

Finally, the econometric models themselves appear to be in conflict with each other. For example, in the basic model proposed by Glosten and Harris (1988), the carrier of asymmetric information is the signed volume, whereas Huang and Stoll (1997) and Madhavan, Richardson, and Roomans (1997) argue that it is the trade sign that is asymmetrically informative. When the econometric models disagree on the variables that reflect adverse selection, conflicting interpretations of empirical results are inevitable.

This paper recognizes that a broader framework is needed to clarify the notion of informed trading. We categorize market players into three groups according to their ability in acquiring and digesting information speedily. Whenever there is some sort of a divide that differentiates traders, there will be information asymmetry. Private signal is not the only source. As in Green (2004), different interpretation of the same *public* information could lead to information asymmetry among dealers of U.S. Treasury securities. This broader framework is useful for reconciling some of the conflicting findings in the literature.

Instead of rescinding the existing models, we take a constructive approach by first acknowledging that the customary definition of informed trading is inadequate. This paper suggests that one can better understand the empirical results documented in Easley, Hvidkjaer, and O'Hara (2002) and Green (2004) when a broader framework of informed trading is employed. Within this broader framework, this paper offers a synthesized model to resolve the conflicts. Instead of treating the variables as mutually exclusive, a natural approach is to take both signed volume and trade sign as explanatory variables. It is noteworthy that using one without the other will lead to over-loading on the single variable and thus result in biased parameter estimates. Therefore, it may well be that the adverse selection costs estimated in the literature are biased because some relevant variables are not included. This could potentially explain why Neal and Wheatley (1998) and Van Ness, Van Ness, and Warr (2001) find the estimates inconsistent with other proxies for information asymmetry.

The main thrust of this paper is to provide evidence that the information structure of a firm relates consistently to a novel measure that emerges from the joint estimation. Specifically, we find that analysts and equity option markets play a significant role in reducing the level of information asymmetry in the stock market. Since information asymmetry is related to the cost of capital, our

findings indicate that it is sensible for firms to implement disclosure policies that attract not only more traders and analysts but also option writers.

In addition to trade sign and signed volume, we include trade-to-trade duration and a signed version of this duration in our specification. The inclusion of these variables is motivated by Glosten and Milgrom (1985), Diamond and Verrecchia (1987) and Easley and O'Hara (1992). In their theories, the time interval between consecutive trades and the associated trade sign in response to either good or bad news contain information as well. Our findings indicate that signed duration also captures asymmetric information.

The proposed asymmetric information measure is consistent with two standard features of financial markets. The measure registers higher values for trades executed during NYSE's opening hours and lower values in the late afternoon. More importantly, the measure can quantify daily level of informed trading and thus is useful in studying changes in the level surrounding a scheduled information event. We find that the level of asymmetric information changes after firms release their quarterly earnings. The level is slightly higher before the announcement. It decreases monotonically until one to two days after the news release. This decline is observed regardless of whether earnings surprises or meets analysts' expectation. For negative surprises in particular, the decline in the level of information asymmetry is more pronounced.

This paper is organized as follows. The next section discusses the information structure of a firm and clarifies the notion of informed trading. A natural measure of information asymmetry is proposed. Data used in our empirical study are described in Section II. Section III reports the empirical findings based on daily parameter estimates. Section IV documents the relations of our measure of informed trading with variables that are used as proxies for the information channels of a firm. In Section V, we summarize the findings and conclude the paper.

## **I. Informed Traders and Models of Informed Trading**

A variety of material information is generated by firms' managers, financial service providers and government agencies. In the event of delisting or takeover, the terminal value of a firm is material information. Quarterly financial results and forward guidance, major contracts, changes in dividend payout, capital reductions, private placements, stock splits and so on are important news, especially when the element of surprise is substantial. In addition, index reconstitutions as well as some macroeconomic numbers are also monitored by traders.

With regard to these news, which do not occur everyday for a given stock, this section attempts a classification of traders to fine-tune the terms “informed” and “uninformed” used in the literature. Finally, we propose a synthesized model to measure the extent of informed trading.

## **A. Who are Informed and Who are Uninformed?**

In Harris (2003), a trader is said to be informed if she can arrive at reliable conclusions about whether financial instruments are fundamentally overvalued or undervalued. Informed traders understand intrinsic values better than other traders because they have better access to fundamental data and can better analyze the implications from their data. To make this notion of relatively informed and relatively uninformed trading operational, we consider three types of traders.

Obviously, company insiders are the most informed. Since their transactions are regulated under the insider trading laws, they are deterred from trading on material information. Of course, unscrupulous insiders can tip others and trade through proxies. In addition, espionage on material information by company employees, associates or outsiders as well as inadvertent leakage prior to public announcements can happen. For convenience, this category of informed traders are referred to as insiders, which includes connected persons and people who obtain pre-release material information. Officers of government agencies who prepare and report key macroeconomic statistics that have bearing on the financial markets are also insiders. Similarly, executives responsible for index reconstitutions are in this category as well. The signal they receive is most precise. A common feature of this group of traders is that they possess private information before it is made public.

The second type of relatively informed traders is institutional investors. These traders know that their trading activity can move prices. They also know that their analysts’ forecasts, ratings and recommendations are influential. Therefore, even in the absence of firm-specific information, their discretionary portfolio rebalancings affect market prices. Typically, they have access to information systems and news feeds that allow them to gain a better understanding of not only the firms but also the macroeconomic conditions and real-time trades and quotes. Included in this category are designated market makers with inventories. They too attempt to obtain information from news and reports to form reliable valuation of the companies they specialize in. If institutional traders and market makers were not diligent in information gathering to gain deeper insights on the firms and the overall market, they would incur losses and go out of business. These traders are constantly on the look out for insiders’ private information in the order flows. In fact, Anand

and Subrahmanyam (2005) find that market intermediaries are informed traders as their trades account for a majority of price discovery in spite of trading less than their clients.

The third type of relatively informed traders are small and retail investors. They are mindful that their trades will not move prices. Nevertheless, they too strive to obtain public announcements of firm-specific information as soon as they are released. More importantly, they also monitor the trades and quotes closely to make real-time trading decisions. Skillful day traders who trade for a living fall under this category. In addition, managers of small funds whose trades are not large enough to create an impact are also considered as small traders. They become informed by reading charts, company and analysts' reports, investment magazines as well as newspapers.

Almost surely, every trader will examine past and prevailing prices before they submit an order. Every market participant is informed to a certain extent. But, the lack of sufficient resources and real-time analytical expertise makes a difference. Retail investors who cannot devote full time to monitor market pulses are uninformed traders most of the time. They do not understand fundamental values better than other traders because even if they have access to fundamental data, they cannot decipher the implications reliably. Their trades are noise because their opinions do not constitute a reliable valuation of the securities and market conditions. On the contrary, if retail and small investors spend time and effort to form reliable opinions about the value and the price trend, they will become less uninformed. Conversely, institutional investors may at times make investment mistakes so that their trades are effectively no different from noise. In other words, every trader except the insider can become a noise trader.

We stress that institutional traders including the market makers have vested interests to know the fundamental values and the market conditions. They trade strategically for liquidity and profit. Small and retail investors are as motivated to stay informed but they do not have the economy-of-scale advantage of institutional traders.

More importantly, even when insiders abstain from trading, information asymmetry still exists in the other two categories of traders. The main reason is that these outsiders have different capabilities and speed to acquire and process public information. Obviously, traders who trade for a living will expend greater effort learning whether a signal (announcement) has occurred. If it does occur, they will analyze it to determine whether it is a good or bad signal before the trading session. Uninformed traders, in contrast, are not able to form a correct interpretation of the signal even if they know that the signal exists.

Therefore, it is plausible that the ability to create order imbalance brings about a dichotomy between the informed and the uninformed. The results in Easley, Hvidkjaer, and O'Hara (2002) may be interpreted consistently under this broader framework of informed trading. The average value of about 19% of informed trading found by the PIN model may be reflecting the information asymmetry primarily among the institutional traders, small and retail investors, and not so much whether some of them have insider information. The higher-than-expected adverse selection costs in Neal and Wheatley (1998) may also be attributable to traders' different abilities in evaluating closed-end funds' premiums or discounts. Changes in the dividend payout and stock splits may also cause traders to interpret the signals emitted by closed-end funds differently.

Transactions themselves are also informative in reflecting the forces of supply and demand. In our framework, market makers are informed on the net demand of buy and sell, which helps them to set the quotes accordingly. Indeed, Green (2004) suggests that primary dealers of Treasury bonds have different interpretations of newly released macroeconomic statistics. They also have different order flows from their clients. Together, these differences give rise to information asymmetry among these dealers.

An implication of transactions as indirect news is that information asymmetry should be higher at the beginning of the trading day and lower toward the end of the trading day. Most U.S. firms announce price-sensitive information in the evening or before the opening bell. Institutional and small investors are presumably more capable in digesting new information speedily and effectively. Their re-evaluation of the firm is manifested in transactions, especially during the opening hours of the trading day. As more information is incorporated through transactions, initially uninformed traders and market makers become more informed<sup>3</sup> on the implications. Therefore, the level of information asymmetry should be higher at the beginning of the trading day and it declines as trading approaches the closing hour.

## **B. Economic Theories of Informed Trading**

In the context of this broader interpretation of relatively informed versus relatively uninformed traders, we turn to the discussion of several market microstructure theories. The motivation is to identify variables that reflect informed trading. Most theories pitch the informed traders against

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<sup>3</sup>Learning from transactions is a shared feature of many notable theories of market microstructure. Examples are Kyle (1985), Admati and Pfleiderer (1988) and Foster and Viswanathan (1990).



the uninformed market makers<sup>4</sup>. For example, in the sequential framework of Glosten and Milgrom (1985), informed traders maximize the profit by trading as often as possible. An implication is that signed duration reveals information asymmetry. Their trading direction will affect the price when it is still not at the full-information level. Glosten and Milgrom (1985) further argue that the order size can be normalized to one. Thus, trade sign rather than volume is asymmetrically informative.

This proposition is contrary to the model in Kyle (1985). Under the batch auction trading, the monopolist market maker strives to infer whether some of the orders are submitted by an insider<sup>5</sup> prior to setting a price. The linear equilibrium solution of the Kyle model suggests that signed volume is informative in determining the transaction price. He and Wang (1995) smoothen the sharp dichotomy between insiders and outsiders with the notion of differential information. In their framework, information includes not only new private signals but also public announcements and market prices. Even the private information is differential. Each informed trader has some information that others do not know. An implication of their theory is that signed volume reflects information asymmetry.

Easley and O'Hara (1987) develop a structural model with the market makers and the uninformed traders not knowing whether an information event has occurred. In their theory, the signal is assumed to occur before the trading day begins. Only the informed traders observe the signal. The equilibrium structure of the Easley-O'Hara (1987) model is more complicated, but the implication is quite the same as the previous two theoretical models. Both trade size and trade direction reveal asymmetric information.

Economic considerations in Glosten and Milgrom (1985), Diamond and Verrecchia (1987) and Easley and O'Hara (1992) suggest that durations are indicative of informed trading. In particular, when even the existence of information event is uncertain, Easley and O'Hara (1992) demonstrate that the lack of trade provides a signal to market participants that there is no information. It follows that the time between trades contains at least this piece of information and thus no longer exogenous to the efficient price process. Longer duration between consecutive trades is associated

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<sup>4</sup>The "uninformed market makers" in most microstructure theories are mainly the uninformed limit-order traders. The designated market makers intermediate as brokers. On the NYSE, for example, specialists' participation rate is about 11.4% on average between year 1973 to 2003 with a standard deviation of 1.8% (See NYSE Fact Book). As discussed earlier, some traders are uninformed relative to other informed traders not because the latter necessarily have insider information but because they are able to arrive at reliable conclusions about the stock valuation more quickly and more accurately.

<sup>5</sup>Kyle remarked that the term "insider trading" used in Kyle (1985) was unfortunate during a seminar at the 12th Conference on the Theories and Practices of Securities and Financial Markets held at Kaohsiung, Taiwan.

with a lower level of informed trading<sup>6</sup>. This result is the opposite of the theoretical prediction by Diamond and Verrecchia (1987). Long duration signals bad news because informed traders cannot sell short<sup>7</sup>.

Whichever the case, the trade that occurs after a long duration may signal that news has arrived. If it is good news, then buyer-initiated trades are more likely to occur, and vice versa. Therefore, not only is the duration but also the direction of that trade, which reflects the news direction (good or bad), is also important. It is plausible that *signed* duration provides a different dimension to examine the information content of a trade that occurs after a long duration. Indeed, Dufour and Engle (2000) empirically demonstrate that signed durations do affect price updates.

As a summary, these theories suggest that at least trade direction, signed volume and signed duration are variables that reflect asymmetric information. This paper makes a hypothesis that relatively uninformed traders learn from these pieces of information from transactions earlier in the trading day and become relatively less uninformed. Consequently, the asymmetric information gap between the initially informed traders and the uninformed traders becomes narrower. It follows that the level of information asymmetry should become lower toward the later part of the regular trading hours.

## C. Empirical Specification

Most empirical models of adverse selection costs, such as Glosten-Harris (1988), Huang-Stoll (1997) and Madhavan-Richardson-Roomans (1997), are motivated by these microstructure theories. For ease of exposition, these three empirical models are henceforth referred to as the GH model, the HS model and the MRR model, respectively. They start from Roll (1984)'s formulation of the transaction price:

$$P_i = M_i + C Q_i . \tag{1}$$

In words, the transaction price  $P_i$  of  $i$ -th trade is postulated to equal the sum of the unobservable efficient price  $M_i$  and the transitory transaction cost  $C$ . The trade sign  $Q_i$  is one or minus one for buyer- or seller-initiated transactions, respectively.

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<sup>6</sup>Note that Easley and O'Hara (1992) do not predict the reverse case that short duration is necessarily associated with a higher level of information asymmetry.

<sup>7</sup>Note that Diamond and Verrecchia (1987) do not suggest that short duration is necessarily good news.

By definition, the unobservable efficient price is a random walk given by

$$M_i = M_{i-1} + u_i. \quad (2)$$

Since  $u_i$  affects the efficient price directly, it contains information impounded by the  $i$ -th trade. Note that all the earlier information from the  $(i-1)$ -th trade and recursively the  $(i-2)$ -th trade and so on is already incorporated in  $M_{i-1}$ . For example, lagged trade sign  $Q_{i-1}$  and signed volume  $X_{i-1}$  are already in the previous efficient price  $M_{i-1}$ .

Depending on the assumptions made for the random component  $u_i$ , these three models are obtainable from equation (1) as variants of the following canonical form:

$$\Delta P_i = C \Delta Q_i + u_i, \quad (3)$$

where  $\Delta$  is the first-order difference operator. To make empirical estimation possible, all the three models rely on this equation with different postulates for  $u_i$ .

If one regards equation (3) as the main econometric specification, then it boils down to identifying the relevant explanatory variables for  $u_i$ . In the GH model, signed volume  $X_i$  is the carrier of information asymmetry. By contrast, trade sign  $Q_i$  is the variable that reveals informed trading in the HS and the MRR models. To avoid misspecification, it is natural to admit both trade sign  $Q_i$  and signed volume  $X_i$  as explanatory variables rather than favoring one over the other. Therefore, we postulate that the innovation  $u_i$  of efficient price in equation (2) is

$$u_i = b_1 Q_i + b_2 X_i + b_3 Q_i \Delta T_i + b_4 \Delta T_i + \epsilon_i. \quad (4)$$

We also examine whether inter-trade duration<sup>8</sup>  $\Delta T_i$  and signed duration  $Q_i \Delta T_i$  reflect informed trading. As discussed earlier, these two variables are motivated by economic theories that emphasize the information role of time interval between consecutive trades. The residual  $\epsilon_i$  is the innovation in market participants' beliefs due to new information not captured by the  $i$ -th trade.

With the innovation  $u_i$  specified as in equation (4), we obtain from equation (3) the following specification to explain intra-day stock price change:

$$\Delta P_i = C \Delta Q_i + b_1 Q_i + b_2 X_i + b_3 Q_i \Delta T_i + b_4 \Delta T_i + \epsilon_i. \quad (5)$$

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<sup>8</sup>The duration  $\Delta T_i$  is a relevant variable as it captures the drift in the efficient price  $M_i$ . In this context,  $b_4$  is the drift rate of the efficient price process.

This econometric model follows the traditional path pioneered by the GH, HS and MRR models. The inclusion of duration and signed duration extends these three models to capture information asymmetry that is revealed in trade frequency. The first term  $C\Delta Q_i$  reflects the transitory component, whereas the remaining four terms jointly explain a portion of the price change that is motivated by informed trading.

From the perspective of equation (5), the three models discussed earlier have the problem of omitted variables. In the HS and the MRR models, the signed volumes  $X_i$  as well as the duration  $\Delta T_i$  and signed duration  $Q_i\Delta T_i$  are omitted. For the GH model, the same problem occurs. From the standpoint of econometrics, when all the relevant variables are not specified, the parameter estimates are likely to be biased.

On the other hand, one may suspect that some variables in equation (5) are irrelevant. However, in this case, there is no bias in the parameter estimates even if some variables are irrelevant. The drawback, however, is that the estimators for the parameters are inefficient. Nonetheless, the estimator  $\hat{\sigma}^2$  for the variance of the residual  $\epsilon_i$  is unbiased. This property is crucial in ensuring that the  $R^2$  of equation (5) is also unbiased, since it is a linear function of  $\hat{\sigma}^2$  (see Maddala (1977) and Maddala (2001)).

Equation (5) also allows us to investigate which of the variables have more explanatory power from their Newey and West (1987)  $t$ -statistics. This test is useful in ascertaining whether, for example, trade size is more important than trade sign in capturing asymmetric information.

If the stock price change is purely frictional and void of information, the innovation  $u_i$  of equation (3), which is nested in equation (5), will be pure noise. Namely,  $u_i$  and  $\epsilon_i$  of equation (5) do not yield statistically different residual sum of squares in this circumstance. Their respective  $R^2$  values, denoted as  $R_c^2$  for equation (3) and  $R_{\text{all}}^2$  for equation (5), will not be much different as a result. Conversely, when the four variables of  $u_i$  capture the price impact of a trade, then  $R_{\text{all}}^2$  will be larger than  $R_c^2$ .

To quantify the joint explanatory power contributed by  $Q_i$ ,  $X_i$ ,  $Q_i\Delta T_i$  and  $\Delta T_i$  in equation (5), we consider the following relation:

$$1 - R_{\text{all}}^2 = (1 - R_{\text{asy}}^2)(1 - R_c^2), \quad (6)$$

where  $R_{\text{asy}}^2$  is the additional goodness of fit contributed jointly by the four variables predicated to reflect informed trading. This equation is basically an identity of linear regression rather than

an empirical relation. As equation (3) is nested in equation (5), the unexplained portion  $1 - R_c^2$  in equation (3) will be reduced by a factor given by  $1 - R_{\text{asy}}^2$  when four variables are added. The product of these two quantities equals  $1 - R_{\text{all}}^2$ . This argument is adapted from Maddala (2001).

Instead of using the estimates for  $b_1, b_2, b_3$  or  $b_4$  as (absolute) adverse selection costs, one could use  $R_{\text{asy}}^2$  to quantify information asymmetry<sup>9</sup>. This measure summarizes the explanatory power jointly contributed by the four variables. The motivation for this asymmetric information measure is twofold. First, if we use only, for example, the coefficient  $b_1$  of the trade sign to estimate adverse selection costs, then the asymmetric information components captured by  $b_2, b_3$  and  $b_4$  are not accounted for. On the other hand, one cannot simply add these components together because each reflects a different dimension of information asymmetry. Moreover,  $b_1$  is in dollars,  $b_2$  in dollars per share,  $b_3$  and  $b_4$  are in dollars per unit time. The measure of informed trading  $R_{\text{asy}}^2$  has the added advantage that its value is between zero and unity, which makes it possible to interpret it as the proportion of price change that is motivated by informed trading. By using  $R_{\text{asy}}^2$ , this paper resolves the conflict between models that depend on  $Q_i$  only and models that use  $X_i$  only to quantify adverse selection costs. We henceforth refer to  $R_{\text{asy}}^2$  as asymmetric information measure, or AIM in short.

Second, AIM is complementary to PIN and a relative measure proposed in Hasbrouck (1991a). Structural PIN model is estimated with the daily numbers of buys and sells. Nonetheless, price-sensitive information encoded in volume and duration is not incorporated in the PIN model. Also, one has to assume that the parameters needed to construct PIN remain constant over the sample period of, say, 60 trading days or more. Hasbrouck (1991a) and Hasbrouck (1991b) measure asymmetric information in trade innovation with vector auto-regression (VAR) methodology. This is different from our framework based on Roll (1984)'s definition, which is expressed as equation (1). The VAR approach has the advantage that the estimation is robust to the specification of transitory component. But, there is no ground to dispute the sensibility of Roll's definition either, which is widely known to reflect the transitory bid-ask bounce. From the practical standpoint, the data requirement is less demanding with the AIM approach than the VAR approach. This is especially true for less liquid stocks, as they may not have sufficient observations to make VAR estimation feasible on a daily basis. The estimates obtained from VAR may also be sensitive to the number of lags. In some sense, AIM may be considered as an asymmetric information measure that is be-

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<sup>9</sup>The procedures to obtain  $R_{\text{asy}}^2$  are simple. Two separate OLS regressions based on equations (3) and (5) are performed with  $y$  intercepts included in the specifications. Using the two coefficients of determination  $R_c^2$  and  $R_{\text{all}}^2$ ,  $R_{\text{asy}}^2$  is obtained from equation (6).

twixt and between the structural economic (such as PIN) and the reduced-form (such as Hasbrouck (1991a) and Hasbrouck (1991b)) models<sup>10</sup>.

## II. Data

The sample period of our study is from January 2, 2003 through December 31, 2003, a total of 252 trading days. The reason for choosing year 2003 is that data such as the number of shareholders needed in our analysis are not as widely obtainable for earlier years. Another reason is the need to control for microstructure noise generated by price discreteness. After February 2001, the effect of price discreteness should be considerably smaller compared to the pre-decimal tick-size regimes. Moreover, by 2003, traders should have become accustomed to trading with the minimum tick size of one cent.

From CRSP database, a sample of NYSE common stocks is taken. Firms with negative stock prices or market capitalizations are excluded. For firms with more than one class of security, we use TAQ's master file to cross-examine and choose the one that is representative of the firm according to the CUSIP as well as the security's name. With all these filters, the final sample size is 1,461 stocks. Panel A of Table I reports the descriptive statistics for these NYSE common stocks.

Intra-day trades and quotes are obtained from TAQ. We sign the trades based on the "tick test."<sup>11</sup> In the same panel, we tabulate the descriptive statistics for the trading activity. Seller-initiated transactions are indicated with negative statistics. Annual data for the number of shareholders and book values are extracted from Compustat. The number of analysts following a firm is derived from I/B/E/S. Panel A of Table I also provides the descriptive statistics for these data. In Panel B, we report the correlation coefficients. As expected, market capitalization correlates positively with both shareholders and analysts but negatively with book-to-market ratio. We also find

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<sup>10</sup>We thank Hasbrouck for this point of view on the synthesized model vis-à-vis the existing models.

<sup>11</sup>Lee and Ready (1991) examine the accuracy of tick test and find that it provides accurate directional inferences for NYSE stocks. To improve the accuracy, they propose an algorithm to sign trades. Their method requires the identification of prevailing quotes. Since quotes are reported with an unknown time lag, they recommend adding five seconds to the quotes' time stamps to synchronize the clocks used in recording the trade and quote tapes. Since Lee and Ready (1991), the NYSE's reporting systems have changed and the frequency of quote updates has increased dramatically. How the quotes lag the trades in year 2003 is by no means obvious. The time lag may be different from one stock to the other. To complicate matter, it is not unusual to observe many quotes with the same time stamp at the one-second resolution. Furthermore, multiple trades can and do occur within the same second. The problem of multiple-to-multiple mapping is quite intractable in the course of our attempt to apply the Lee-Ready algorithm. For these reasons, and also because some quote files are not available for some of our sample stocks on some days, we resort to using the tick test to sign the trades.

that the book-to-market ratio relates negatively with the number of analysts but insignificantly with shareholders. As anticipated, the latter two numbers correlate positively.

Finally, information regarding whether a firm has exchange-traded equity options is obtained from the Options Clearing Corporation.

### III. Estimations and Analysis

For each trading day and each stock, we perform an OLS regression with equation (3), and a GMM regression based on equation (5). The asymmetric information measure  $R_{asy}^2$  is obtained from equation (6). In total, there are 329,187 stock-days in our sample. We plot the time series of daily cross-sectional average AIM values in Figure 1. It is evident that average AIM fluctuates from one trading day to the other.

On May 19, 2003 in particular, estimated AIM is at its peak with a value of 27.79%. After the Group of Seven finance ministers' meeting in France over the weekend, Treasury Secretary John Snow indicated that Washington supported a weaker dollar. On that Monday<sup>12</sup>, however, the White House clarified that there had been no change in its policy supporting a strong dollar. These announcements probably create a larger wedge between the informed and the uninformed, thus a larger value of AIM.

Next, the distribution of these 329,187 AIM values is plotted in Panel A of Figure 2. On average, this measure of informed trading is 19.7% with a standard deviation of 9.2%. In other words, after controlling for transitory component  $C$ , the last four explanatory variables in equation (5) jointly explain about 20% of the variation in the high-frequency price change. It follows that about 20% of the trades in our sample of NYSE firms are associated with informed trading.

Panel B displays the histogram of the annual average AIM values for our 1,461 sample stocks. The cross-sectional average value over the sample period is 20.5% for these stocks. This average value is large if information asymmetry is caused only by insiders who trade illegally ahead of public disclosures. In other words, if 20% of the trades contained purely insider information, then it would imply that U.S. insider trading laws fail to be a deterrent and their enforcement is ineffective. But, if one uses the broader framework discussed in Section I.A, where some traders are

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<sup>12</sup>The market closed out the day with steep losses. The Dow Jones Industrial Average Index declined 185.58 to 8,493.39. The S&P 500 Index dropped 23.53 to 920.77, while the Nasdaq Composite Index plummeted 45.76 to 1,492.77. The yield of 10-year Treasury note also declined 8/32, yielding 3.45%.

better informed by virtue of their superior ability in pricing the fair value of a stock as well as in understanding the prevailing market conditions, then this percentage of information asymmetry appears to be a reasonable estimate.

## A. Relative Importance of Explanatory Variables

To examine the relative importance of informed trading variables, we count the numbers of statistically significant coefficients in equation (5). The results are reported in Table II. We find that  $b_1$ , the coefficient of trade sign  $Q_i$ , is the main contributor. At the two-tail 5% and 1% levels,  $b_1$  is, respectively, 92.65% and 87.33% of the times significant. Therefore, the HS or the MRR model accounts for a larger portion of the variation in the non-transitory price change.

Results also show that signed volume  $X_i$  and signed duration  $Q_i\Delta T_i$  are the next two most important explanatory variables. While the role of  $X_i$  has been well studied, it appears that the importance of signed duration has been overlooked in the literature on adverse selection costs. The coefficient of the duration  $\Delta T_i$ , however, is significant only 5.77% of the times at the 1% level. This is three times lower than signed duration's 19.25%. There is therefore some evidence to suggest that it is not the duration per se but the signed duration that captures informed trading. As a robustness check, intra-day observations are pooled over a month. Same regressions are performed, but the results do not change the conclusions.

As shown in Panel C of Table II, among the parameter estimates significant at the 1% level, more than 93% of  $b_1$ ,  $b_2$  and  $b_3$  are positive. The positivity of these parameter estimates for the trade sign, the signed volume and the signed duration, respectively, lends support for their roles in revealing asymmetric information. In particular, positive loading on the signed duration is consistent with the notion that after a long duration, a trade has more impact in moving the stock price in the direction of its trade sign. For example, a buy 100 seconds later has more price impact than a buy with a duration of 1 second.

## B. Is Trade Sign Alone Sufficient to Reflect Information Asymmetry?

With  $Q_i$  found to be the most important carrier of informed trading, we examine whether the other three variables are redundant. Therefore we consider

$$\Delta P_i = C^* \Delta Q_i + b_1^* Q_i + \epsilon_i^*. \quad (7)$$



In addition to comparing  $b_1^*$  with  $b_1$  from the synthesized model (equation (5)) directly, the two ratios defined as

$$r^* \equiv \frac{b_1^*}{C^* + b_1^*}; \quad r \equiv \frac{b_1}{C + b_1} \quad (8)$$

are also compared. We estimate the parameters daily using intra-day data for each stock.

To ascertain whether there is a bias in  $b_1^*$  due to variable omission, we examine a subsample of 1,409 stocks that have more than 10 days of daily estimates. For each stock, a t-test is performed to compare the daily  $b_1^*$  and  $b_1$  estimates on the null hypothesis of equal mean. Table III reports the results by market capitalization quintile. For every quintile, the first to 99-th percentile statistics for  $b_1^*$ ,  $b$  and the  $t$ -statistics are tabulated in Panel A. We find that estimated  $b_1^*$  and  $b$  values are larger for smaller capitalization stocks, as anticipated. Within each quintile, we observe that  $b_1^*$  is larger than  $b$  for all the percentile values.

Even at the first percentile, the two-tail  $t$ -statistic of the two-population mean test in each quintile is already above 2. This result suggests that irrespective of firm size, the means of  $b_1^*$  and  $b_1$  are not the same, and  $b_1^* - b$  is statistically positive. We also conduct the non-parametric Wilcoxon signed rank tests. The  $z$ -statistics for all quintiles indicate that the  $p$  values are zero. Therefore, this paper concludes that the medians of  $b_1^*$  and  $b_1$  are not the same either. All these results provide evidence to suggest that  $b_1^*$  has an upward bias. As a robustness check, the two ratios  $r^*$  and  $r$  are also compared for each stock. The summary statistics are reported in Panel B. Again, we reach the conclusion that  $r^*$  tends to be larger than  $r$ .

These analyses indicate that although the trade sign  $Q_i$  is most important in explaining the price change with 92.65% of the coefficients significant at the 5% level, the other three variables cannot be excluded. Overall, the average upward bias of 6.14 percentage points in  $r^*$  is statistically and economically significant.

Turning to the question of which specification has a better goodness of fit as measured by the adjusted  $R^2$ , we find that the *adjusted*  $R_{\text{all}}^2$  for equation (5) is on average larger than the adjusted  $R^2$  for equation (7) by 2.87%. This larger value is statistically significant. The confidence interval obtained in the two-tail t-test is from 2.82% to 2.92%. The null hypothesis of equal adjusted  $R^2$  value is rejected. In addition, non-parametric rank sum test supports the alternative hypothesis of adjusted  $R_{\text{all}}^2$  being greater than adjusted  $R^2$  for equation (7). All these results suggest that specification (5) is empirically a better model than equation (7). Therefore,  $Q_i$  alone is not sufficient to reflect the other dimensions of informed trading.

Conversely, one may argue that contributions from the other parameters in equation (5) should be added to  $b_1$ . But, this is not possible because, as mentioned earlier,  $b_2$  depends on the unit used for trade size, and  $b_3$  and  $b_4$  on the unit employed to measure time. In the GH model, a unit of a thousand shares is used. However, there is no a priori reason why a thousand shares is a suitable aggregate unit. If the number of shares is used as the unit instead,  $b_2$  will be a thousand times smaller because the regression is linear. As a result, the asymmetric information cost contributed by  $b_2$  will be negligibly small compared to the transitory component  $C$ . The same argument applies with respect to  $b_3$  and  $b_4$ . This observation provides further motivation for using a unit-independent quantity such as AIM as a measure of asymmetric information.

### **C. Intra-Day Analysis**

An implication of the notion of relatively informed trading discussed in Section I.A is that AIM should be higher at the beginning but lower at the end of trading day. To test this hypothesis, NYSE's regular trading hours are divided into seven periods and estimation statistics are obtained for all stocks in the first three months (61 trading days) of 2003. Following Hasbrouck (1991b), three months worth of observations of each stock are then pooled together and an AIM value is estimated for each intra-day period.

Summary statistics for all sample stocks are presented in Table IV. On average, there are more observations at the opening and at the closing hour. This is the well-known U-shaped regularity of trading activity. The first half hour has the highest level of information asymmetry. On average AIM is 20.54%. This finding is consistent with the notion that over-night information as well as pre-opening news are processed and interpreted differently by traders. As trading progresses, more traders become aware of the information and its interpretation, either directly or indirectly by observing the publicly available trades and quotes in the earlier hours. As the regular trading hours approach 4 P.M., more traders become less uninformed as news and their interpretations are more clearly manifested in the intra-day time series of transactions. Consequently, the level of information asymmetry drops.

When this broadly-defined information asymmetry decreases, AIM should become smaller. The monotonic decrement is observed from Table IV, which shows a higher level of informed trading at the beginning and lower level at the closing. The drop from the first period (9:30 A.M. to 10 A.M.) to the second period (10 A.M. to 11 A.M.) is 2.97 percentage points. From 11 A.M. to 3 P.M., the decrements for the four hourly periods in this time interval are 0.98, 0.29, 0.28 and 0.19 percentage

points, respectively. Average AIM declines further by 1.18 percentage points when trading enters the last regular hour (3 P.M. to 4 P.M), which yields the smallest average value of 14.65%. Compared to the first half hour, the last trading hour's AIM is 5.89 percentage points smaller, a reduction of 28.7% in the level of information asymmetry. These results are generally consistent with the impulse response analysis and an absolute measure (trade-correlated component of the efficient price change) reported in Hasbrouck (1991b).

Monotonic decrements are also observed for  $b_1$  of equation (5). The values of these two parameters are larger at the beginning than at the end of trading. By contrast,  $C$  is fairly constant throughout, although it is also lower in the last two trading hours. If one interprets  $2 \times (C + b_1)$  as the implied spread, this empirical outcome is consistent with the well-documented fact that bid-ask spreads are larger at the beginning but smaller at the end of trading day. We also note that the average Newey-West  $t$ -statistics for  $b_1$  are large. This is consistent with our earlier findings that trade sign is the main variable that reflects informed trading.

Similar pattern is observed for  $b_2$ , the coefficient of signed volume. Compared to  $b_1$ , the average values of  $b_2$  across the intra-day time periods are more than a thousand times smaller. For example, the average value of  $b_1$  is 1.06 cents per share in the first period while  $b_2$  is only 0.00052 cents per share in the same period. This suggests that while  $b_2$  is statistically significant, on the per-share basis, it is not economically significant as compared to  $b_1$ .

For signed duration, we observe a U-shaped-like pattern. The 1 to 2 P.M. time slot has the smallest average value for  $b_3$ . Its value declines from morning and recovers somewhat toward the late afternoon. A relatively long signed duration in the morning has more price impact than a long signed duration in mid day. When trades are concentrated as in the first half hour, even a slightly long signed duration contains relatively more information that moves the price in the direction of the trade. Average  $t$ -statistics for  $b_3$  suggest that signed duration is significant at the 1% or 5% level over the seven time slots. Compared to  $b_3$ , the coefficient  $b_4$  of (unsigned) duration is about ten times smaller in magnitude. But a U-shaped-like pattern for the absolute value of  $b_4$  is also observed.

#### **D. Daily Variation and Earnings Announcement**

Another implication of broadly defined informed trading is that scheduled earnings announcements should affect the level of information asymmetry. To the extent that public disclosures are infor-

mative, and that traders have different interpretations, the level of information asymmetry before an earnings announcement should be different from that after the news release. Having a daily estimate such as AIM makes this test possible.

For each earnings announcement, six daily AIM estimates are singled out in this comparative analysis. Two estimates are immediately before the announcement, two on the announcement day itself and the following day, and the remaining two on the second and third trading days after the earnings announcement date. Three periods of two days each are considered. For convenience, they are referred to as Before, During and After.

For each announcement date, average AIM values are obtained for these three periods. For the Before period, a ratio  $\alpha_b$  is defined as follows:

$$\alpha_b \equiv \frac{\text{Average AIM for Before periods}}{\text{Average AIM for days not in Before, During and After periods.}} \quad (9)$$

The corresponding ratios for During and After are defined in the similar fashion. They are denoted as  $\alpha_d$  and  $\alpha_a$ , respectively. These ratios are meant to indicate the level of information asymmetry with respect to the average AIM for other days not around any earnings announcements. Given the sample period, the average AIM for these other days is constant for each stock in year 2003. If the  $\alpha$  ratio becomes larger (smaller) than one, then the level of informed trading is said to be higher (lower) in that two-day period relative to other days.

In total, there are 4,748 quarterly earnings announcement dates in year 2003 for our sample stocks that have analysts covering them. The median value of analysts' forecasts for the nearest quarter (prior to the announcement dates) is employed to indicate the consensus forecast of earnings per share (EPS). If the difference between the actual EPS and the consensus EPS is positive, then there is an upside surprise. Conversely, a downside surprise occurs when the difference is negative. When the actual EPS and the consensus EPS coincide, the quarterly firm's report is said to have met the analysts' expectation. In our sample, there are 1,373 downside surprises; 811 reports are in line with the expectation; and 2,564 earnings results beat the market.

From Panel A of Table V, one sees that before the earnings announcement, cross-sectional average  $\alpha_b$  is 1.00 with a standard deviation of 0.26. Median  $\alpha_b$  is 0.97. In other words, average AIM for the two days in the Before period does not appear to be that different from the normal average AIM value. Whether the earnings exceed, meet or fall short of consensus EPS does not give rise to different  $\alpha_b$  values in the Before period.

However, average  $\alpha_d$  and  $\alpha_a$  values of 0.95 and 0.94, respectively, are different from average  $\alpha_b$ . These two average values for the During and After periods are generally lower, by about 5 to 6% with respect to the normal AIM level. In particular, earnings that disappoint analysts have the largest decline. Average  $\alpha_a$  for downside surprises is 0.93 and the median is 0.90 for the After period. It appears that after the company has released a downside surprise, the information asymmetry gap between the informed and the uninformed generally narrows. Traders who are initially less informed learn more from negative surprises so that their disadvantage relative to informed traders is mitigated.

This possibility seems to be consistent with Chan, Karceski, and Lakonishok (2003). They find evidence that earnings and forecast are managed in such a way that non-negative surprises occur much more frequently than what is due solely to chance. Our cross-sectional sample also exhibits a similar pattern. Non-negative surprises are 2.46 times of negative surprises. Therefore, it could be that non-negative surprises have become less informative. This explains why the  $\alpha$  ratios a day after the announcement for non-negative surprises do not decline by as much as the  $\alpha$  ratio for negative surprises. In other words, earnings announcements with bad news remove more information asymmetry among traders than with good or “expected” news.

To examine whether the differences before, during and after an announcement are statistically significant, Wilcoxon’s signed rank tests of equality of medians and two-population mean tests are conducted. The test statistics based on 4,748 observations are tabulated in Panel B, along with the sub-samples’ test statistics for downside surprises, in-line earnings and upside surprises. Most of these statistics suggest that the differences are significant at the 1% level. Furthermore, AIM becomes lower in the During period, i.e., earnings announcements are immediately useful in reducing information asymmetry. From the During period to the After period, the declines in AIM estimates are not as significant. But when the  $\alpha$  ratios for Before and After periods are directly compared, the evidence of information asymmetry reduction becomes clearer.

To see the daily changes in AIM, cross-sectional averages of  $\alpha$  ratios are obtained for a few days surrounding the announcement date. Figure 3 plots three curves that correspond to upside surprises, expectations met and downside surprises. The decline in the  $\alpha$  ratio is largest for earnings that disappoints the market. On the whole, the curves slope downward three trading days before announcement. Earnings that met and beat analysts’ consensus forecasts slope upward two days after the announcement. For earnings that have downside surprises, the day immediately after the announcement has the lowest AIM. Thus, a U-shape-like pattern is observed over these eight days.

In summary, daily AIM estimates allow one to answer the question of whether earnings announcement affects the information asymmetry among traders. There is evidence to support the hypothesis that the level of informed trading changes around the announcement date. The level is lower during and after the public disclosure. If quarterly earnings is below analysts' expectation, the level declines the most — by about 7% on average.

## IV. Determinants of Asymmetric Information Measure

This section examines the cross-sectional determinant of AIM. We study the relations between AIM and variables that serve as proxies for the information channels. To make the exposition clearer, we define for firm  $j$ ,

$$\text{AIM}_j \equiv \text{Average of daily AIM values of firm } j \text{ over the sample period.} \quad (10)$$

The distribution of 1,461  $\text{AIM}_j$  is plotted in Panel B of Figure 2. Average  $\text{AIM}_j$  is 20.5%, which suggests that this proportion of the intra-day price changes is attributable to asymmetric information.

In the beginning of this paper, we enunciate the information structure of a firm as channels through which information about the firm is revealed to the market, which is reflected in the stock price. The number of traders in this channel determines the channel capacity in revealing the information. Viewed from the perspective of information structure, it is natural to reckon that analysts constitute another channel for the information flow. The bandwidth of this channel is determined by the number of analysts.

At any given time, the stock price represents a consensus valuation by traders. It follows that the equity option market provides yet another channel, as the option price and the stock price are related. Therefore, we consider the following variables that characterize the information structure of firm  $j$ :

- $\text{Shareholders}_j$ : Number of firm  $j$ 's shareholders in logarithmic levels<sup>13</sup>;
- $\text{Analysts}_j$ : Number of analysts following firm  $j$  in logarithmic levels;
- $\text{Option}_j$ : An indicator variable that equals one if the stock of firm  $j$  is an underlying instrument of some options traded in some option exchanges, and zero otherwise.

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<sup>13</sup>The logarithmic scale is used because the number of shareholders varies over a few orders of magnitude in our sample.

The number of shareholders is used as a proxy for the number of traders in the stock market. In general, a larger number of shareholders is likely to correlate with a greater degree of heterogeneity in traders' valuations. A larger base of investors with greater heterogeneity tends to associate with a lower level of information asymmetry, and vice versa. Regression A in Table VI provides a test for this heterogeneity hypothesis. The tabulated  $t$ -statistics in the parentheses are adjusted with Newey and West (1987)'s algorithm to account for potential heteroskedasticity and inter-stock correlations. As anticipated, we find that  $AIM_j$  relates negatively to  $Shareholders_j$  with a coefficient of -1.06.

Next, we consider the information channel characterized by  $Analysts_j$ . It is reasonable to assume that analysts' reports are informative in general. Their reports and forecasts at least raise the public awareness of the firms they are following. Consequently, investors may become more receptive to trade the stocks of these firms. More analysts tend to narrow the information gap between the informed and the uninformed. The level of information asymmetry should be lower when there are more analysts providing their assessments and recommendations. Regression B in Table VI tests the relation between  $AIM_j$  and  $Analysts_j$ . We obtain a  $t$ -statistic of -27.6, which implies that their relation is negative and statistically significant.

We find that  $Analysts_j$  is more powerful in explaining the cross-sectional variation in  $AIM_j$ . The goodness of fit for Regression B is more than 45%. In contrast,  $Shareholders_j$  in Regression A explains only 11.5%. This could be attributable to the possibility that  $Shareholders_j$  is a noisy proxy for the number of traders.

The existence of an option market with the stock as the underlying instrument provides an alternative channel for information flow. Traders who are confident about their valuation may find options attractive owing to the leverage they provide. These informed traders may choose to make a profit not from the stock market but from the option market instead. Chakravarty, Gulen, and Mayhew (2004) employ a vector error correction model to measure the intra-day price discovery in option markets. Their evidence supports the notion that informed investors trade options to take advantage of high leverage. Moreover, they hypothesize that hedging demand by option writers may represent an indirect type of informed trading for the underlying stocks. By having  $Option_j$  as a control variable, our empirical study provides a test for the net effect of option market. If option markets draw informed traders away from the stock market is the primary effect, and if hedging by option market makers is a secondary effect, then one would expect  $Option_j$  to be negatively related to  $AIM_j$ . Conversely, if hedging the underlying stocks by option market makers is the primary effect on the stock market, then  $Option_j$  will be positively related to  $AIM_j$ .

In Regressions C and D, the indicator variable  $\text{Option}_j$  is included in the specification. Consistent with the hypothesis that informed traders may choose to take advantage on the equity option market instead, we find that  $\text{AIM}_j$  is negatively related to  $\text{Option}_j$ . The double-digit  $t$ -statistics for  $\text{Option}_j$  in these two regressions strongly suggest that a stock that attracts option writers and option traders have a smaller amount of information asymmetry on the stock market. The reduction in  $\text{AIM}_j$  due to fewer traders being asymmetrically informed on the stock market outweighs the hedging demand of option market makers.

It is noteworthy that when  $\text{Option}_j$  is included, the loadings on  $\text{Shareholders}_j$  and on  $\text{Analysts}_j$  are reduced. The coefficient for  $\text{Shareholders}_j$  is -0.55 in Regression C as compared to -1.06 in Regression A. Similarly, the coefficient for  $\text{Analysts}_j$  changes from -4.32 to -2.80 when  $\text{Option}_j$  is included. We perform Regression E to further examine the relative effectiveness of the three variables,  $\text{Shareholders}_j$ ,  $\text{Analysts}_j$  and  $\text{Option}_j$  in explaining cross-sectional  $\text{AIM}_j$ . All the coefficients for the three information channel variables are found to be negatively significant.

Finally, we regress  $\text{AIM}_j$  on these three information channel variables along with  $\text{Cap}_j$  (the market capitalization) and  $\text{B/M}_j$  (the book-to-market ratio) in logarithmic levels as control variables. The result is as follows:

$$\text{AIM}_j = 30.1 - 0.166 \text{Shareholders}_j - 2.383 \text{Analysts}_j - 5.026 \text{Option}_j - 0.357 \text{Cap}_j - 0.501 \text{B/M}_j. \quad (11)$$

(23.6) (-2.46)                      (-11.1)                      (-13.1)                      (-2.81)                      (-2.89)

The  $t$ -statistics are shown in the parentheses. The adjusted  $R^2$  of this regression is 58.0%, which is marginally better than 57.1% of Regression E. More importantly,  $\text{Shareholders}_j$  is significant at the 5% level, while  $\text{Analysts}_j$  and  $\text{Option}_j$  are consistently significant at the 1% level for this specification, and for all the regressions reported in Table VI. Therefore, we have evidence to suggest that more traders and analysts following the firm help to reduce information asymmetry, and the option market diverts informed traders from the primary information channel, the stock market. This diversion effect more than offsets the asymmetric information conveyed indirectly by option market makers back to the stock market in their hedging trades.

As anticipated, larger firms do not have as much asymmetric information among traders as smaller firms. We find that higher book-to-market or value firms have a smaller proportion of informed trading. Overall, the more robust relation is with the number of analysts and whether there are exchange-traded equity options on firms shares.



## V. Summary and Concluding Remarks

An understanding of informed trading has implications for financial market regulators, institutional traders and investors at large. In addition, the design of information structure is important in making corporate decisions on how material information should be managed. Since a firm with higher asymmetric information costs tends to have higher capital costs, a market microstructure analysis of informed trading is potentially useful for corporate finance.

We show that existing models of asymmetric information need to control for other variables that are also deemed to reflect informed trading. These models are inconsistent with each other with regard to either the trade size or the trade sign as the variable that captures asymmetric information. This paper jointly examines four variables predicated to reflect informed trading. These variables are trade sign, signed volume, as well as duration and signed duration. Overall, the results indicate that trade sign reflects information asymmetry better than the other three variables.

We quantify the explanatory power of these four determinants of intra-day stock price change. On average, they jointly explain 19.7% of the variation that is attributable to information asymmetry for the NYSE stocks. This paper also provides a more generic framework to interpret informed trading. In our framework, not only are the insiders informed, small investors who can arrive at reliable conclusions concerning the fundamental values of firms are also deemed to be better informed than noise traders. There is information asymmetry even when the trades are not motivated by private information. Transactions per se are informative as well. Our empirical results show that trades after a long duration tend to move stock price in the direction of their trade signs.

Using the proposed asymmetric information measure, we study changes in the level of informed trading around public disclosures of quarterly earnings. A total of 4,748 announcement dates are separated into three groups of upside, downside and no surprises. This paper finds evidence in support of a normal to slightly higher level of informed trading two to three days prior to the announcement. The level decreases monotonically until one to two days after the announcement. Moreover, the decrement is more dramatic for earnings that disappoints analysts' expectation.

As expected, the proposed asymmetric information measure indicates that the level of informed trading is highest during the market open. It decreases monotonically well into the afternoon and the level is the lowest an hour before the closing bell. This result is consistent with the notion that traders learn from past trades in the earlier hours about the stock value. As a result, information

asymmetry becomes less pronounced toward the later trading hours of the day. An implication of this finding is that uninformed liquidity traders have a tendency to trade toward the end of NYSE's regular hours. This result is consistent with Admati and Pfleiderer (1988).

Finally, the empirical findings with a subsample of 1,207 NYSE common stocks in year 2003 support the hypotheses that analysts and equity option markets are helpful in reducing the information asymmetry among traders in the stock market. Specifically, after controlling for firm size and book-to-market value, we find that the asymmetric information measure relates negatively to the number of analysts following a firm. This measure will also be lower if there are exchange-traded options with the firm's common stock as the underlying instrument. These results have practical implications for firms' managers. To improve the information structure, our findings suggest that it is worthwhile to consider ways to attract not only more investors and analysts but also option writers.

## References

- Admati, Anat R., and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3–40.
- Anand, Amber, and Avanidhar Subrahmanyam, 2005, Information and the intermediary: Are market intermediaries informed traders in electronic markets?, Working paper, Syracuse University.
- Chakravarty, Sugato, Huseyin Gulen, and Steward Mayhew, 2004, Informed trading in stock and option markets, *Journal of Finance* 59, 1235–1257.
- Chan, Louis K.C., Jason Karceski, and Josef Lakonishok, 2003, Analysts' conflict of interest and biases in earnings forecasts, Working paper, University of Illinois.
- Copeland, Thomas E., and Dan Galai, 1983, Information effects on the bid-ask spread, *Journal of Finance* 38, 1457–1469.
- Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277–311.
- Dufour, Alfonso, and Robert F. Engle, 2000, Time and the price impact of a trade, *Journal of Finance* 55, 2467–2498.
- Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, 2002, Is information risk a determinant of asset returns?, *Journal of Finance* 57, 2185–2221.
- Easley, David, and Maureen O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69–90.
- Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance* 47, 577–605.
- Foster, Douglas F., and S. Viswanathan, 1990, A Theory of the interday variations in volume, variance, and trading costs in securities markets, *Review of Financial Studies* 3, 593–624.
- Glosten, Lawrence R., and Lawrence E. Harris, 1988, Estimating the components of the bid/ask spread, *Journal of Financial Economics* 21, 123–142.
- Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a market-maker market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.
- Green, Clifton T., 2004, Economic news and the impact of trading on bond prices, *Journal of Finance* 59, 1201–1233.

- Harris, Larry, 2003, *Trading and exchanges: Market microstructure for practitioners*. (Oxford University Press, New York).
- Hasbrouck, Joel, 1991a, Measuring the information content of stock trades, *Journal of Finance* 46, 179–207.
- Hasbrouck, Joel, 1991b, The summary Informativeness of stock trades: An econometric analysis, *Review of Financial Studies* 4, 571–595.
- He, Hua, and Jiang Wang, 1995, Differential information and dynamic behavior of stock trading volume, *Review of Financial Studies* 8, 919–972.
- Huang, Roger D., and Hans R. Stoll, 1997, The components of the bid-ask spread: A general approach, *Review of Financial Studies* 10, 995–1034.
- Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.
- Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.
- Maddala, G. S., 1977, *Econometrics*. (McGraw-Hill, London, England).
- Maddala, G. S., 2001, *Introduction to econometrics, third edition*. (John Wiley, West Sussex, England).
- Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why do security prices change? A transaction-level analysis of NYSE stocks, *Review of Financial Studies* 10, 1035–1064.
- Neal, Robert, and Simon M. Wheatley, 1998, Adverse selection and bid-ask spreads: Evidence from closed-end funds, *Journal of Financial Markets* 1, 121–149.
- Newey, Whitney, and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–798.
- Roll, Richard, 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, *Journal of Finance* 39, 1127–1139.
- Van Ness, B. F., R. A. Van Ness, and R. S. Warr, 2001, How well do adverse selection components measure adverse selection?, *Financial Management* 30, 77–98.

**Table I**  
**Annual Statistics for 1,461 NYSE Firms**

Panel A tabulates the number of common shares outstanding, market price and capitalization as at end of December 2002. These statistics are obtained from CRISP. From Compustat, annual book values are extracted to arrive at the book-to-market ratios. The number of shareholders is also from Compustat whereas the number of analysts is derived from I/B/E/S for stocks that have at least one analyst following the firm. Not all our sample firms had transactions on each of the 252 trading days in year 2003. Firms in the first percentile had only 55.1 days. Annual statistics for the trading activity are based on TAQ. We report seller-initiated transactions in negative numbers. Panel B tabulates the correlation coefficients. All the correlation coefficients are significant at the 5% level except the correlation between the book-to-market ratio and the number of shareholders.

Panel A: Descriptive Statistics

	Unit	Mean	Standard Deviation	1st	25th	Percentile		
						50th	75th	99th
Common Shares	Billions	0.19	0.53	0.005	0.03	0.05	0.14	2.37
Price	\$	23.86	25.53	1.269	10.81	20.62	31.89	77.45
Capitalization	Billion \$	5.29	17.66	0.026	0.35	1.03	3.16	83.34
Book-to-Market $\times 10^3$		0.74	0.71	0.055	0.37	0.59	0.86	3.57
Number of Shareholders	Thousands	36.30	162.21	0.045	1.24	4.67	17.50	667.47
Number of Analysts		11.17	7.94	1	5	10	16	34
Days of Trading		244.1	33.0	55.1	251	252	252	252
Number of Trades	Thousands	105.5	109.4	0.488	25.89	69.30	154.22	505.8
		-87.8	-94.3	-0.415	-20.71	-56.11	-124.94	-440.3
Volume Traded	Millions	1.06	2.09	0.004	0.11	0.36	1.13	10.01
		-0.77	-1.57	-0.003	-0.09	-0.26	-0.80	-7.46
Dollar Volume Traded	Million \$	30.4	63.5	0.015	1.73	7.74	29.98	314.1
		-22.2	-47.7	-0.014	-1.36	-5.60	-21.68	-236.1

Panel B: Correlation Coefficients

	Capitalization	Book-to-Market	Shareholders	Analysts
Capitalization	1	-0.152	0.370	0.388
Book-to-Market		1	-0.032	-0.252
Shareholders			1	0.277
Analysts				1

**Table II**  
**Relative Importance of Variables that Capture Asymmetric Information**

This table reports the summary statistics for the coefficients of the following regression:

$$\Delta P_i = b_0 + C\Delta Q_i + b_1 Q_i + b_2 X_i + b_3 Q_i \Delta T_i + b_4 \Delta T_i + \epsilon_i .$$

The dependent variable is the trade-to-trade price change. The explanatory variables of interest are trade sign  $Q_i$ , signed volume  $X_i$ , signed duration  $Q_i \Delta T_i$  and duration  $\Delta T_i$ . In total, 329,187 GMM regressions have been performed. In Panels A and B, the percentage is computed with this number as the denominator. Panel C uses the numbers in Panel B to arrive at the percentages of positive estimates that are significant at the 1% level.

Panel A: 5% Significance Level

	$b_1$	$b_2$	$b_3$	$b_4$
Number	304,989	143,759	107,362	49,156
Percent	92.65	43.67	32.61	14.93

Panel B: 1% Significance Level

	$b_1$	$b_2$	$b_3$	$b_4$
Number	287,475	89,958	63,376	18,996
Percent	87.33	27.33	19.25	5.77

Panel C: Positive Estimates (1% Level)

	$b_1$	$b_2$	$b_3$	$b_4$
Number	287,424	87,714	59,174	7,188
Percent	99.98	97.51	93.37	37.84

**Table III**  
**Summary Statistics for Comparing the Trade Sign's Parameter Estimates**

This table reports the summary statistics for the parameter estimates in the following two specifications:

$$\begin{aligned}\Delta P_i &= a_0 + C^* \Delta Q_i + b_1^* Q_i + \epsilon_i^* ; \\ \Delta P_i &= b_0 + C \Delta Q_i + b_1 Q_i + b_2 X_i + b_3 Q_i \Delta T_i + b_4 \Delta T_i + \epsilon_i .\end{aligned}$$

In these two specifications,  $\Delta P_i$  is the trade-to-trade price change,  $Q_i$  the trade sign,  $X_i$  the signed volume and  $\Delta T_i$  the trade duration. Residuals are denoted by  $\epsilon_i^*$  and  $\epsilon_i$ , respectively. Quantities of interest are  $b_1^*$  in the first specification, and the corresponding construct  $b_1$  in the second specification. The second specification provides a platform to examine the bias in  $b_1^*$  when the three variables  $X_i$ ,  $Q_i \Delta T_i$  and  $\Delta T_i$  are omitted. For each sample stock that has at least 50 paired sets of estimates, a two-tail t-test for the null hypothesis of equal mean value ( $b_1^* = b_1$ ) is performed. Another t-test is also performed to examine the null hypothesis of  $r^* = r$ . These two ratios are defined by  $b_1^*/(b_1^* + C^*)$  and  $b_1/(b_1 + C)$ , respectively. To present the statistics, the stocks are grouped into quintiles by market capitalization. The first quintile contains 293 smallest market capitalization stocks. For the other four quintiles, each has 292 stocks. The percentile (per) statistics for the values of  $b_1^*$ ,  $b_1$  and the t-test statistics are reported in Panel A. As an example, for stocks in the first market capitalization quintile, the first-percentile value for their  $b_1^*$  estimates is 0.117 cents per share and the 99-th percentile value is 3.85 cents per share. The  $b_1$  estimates are 0.038 cents per share in the first percentile and 3.291 cents per share in the 99-th percentile. Their two-population mean tests'  $t$ -statistics at the first percentile is 2.19 and 10.42 at the 99-th percentile. The corresponding statistics for  $r^*$ ,  $r$  and the test statistics are reported in Panel B. Overall, the large values of  $t$ -statistics in all quintiles provide evidence that irrespective of firm size,  $b_1^*$  has an upward bias relative to  $b_1$ .

Panel A

First Quintile: Smallest Market Capitalization Stocks

	1st per	25th per	50th per	75th per	99th per
$b_1^*$ (in Cents/Share)	0.117	0.540	0.863	1.334	3.850
$b_1$ (in Cents/Share)	0.038	0.367	0.632	1.034	3.291
$t$ -statistic	2.19	3.85	5.00	6.17	10.42

Second Quintile

	1st per	25th per	50th per	75th per	99th per
$b_1^*$ (in Cents/Share)	0.139	0.517	0.819	1.261	3.509
$b_1$ (in Cents/Share)	0.073	0.376	0.615	0.968	2.865
$t$ -statistic	2.97	5.18	6.26	7.60	11.72

Third Quintile

	1st per	25th per	50th per	75th per	99th per
$b_1^*$ (in Cents/Share)	0.110	0.415	0.659	1.018	3.006
$b_1$ (in Cents/Share)	0.068	0.311	0.501	0.785	2.395
$t$ -statistic	2.51	5.83	6.98	8.42	16.03

Fourth Quintile

	1st per	25th per	50th per	75th per	99th per
$b_1^*$ (in Cents/Share)	0.121	0.361	0.529	0.750	1.936
$b_1$ (in Cents/Share)	0.079	0.270	0.406	0.585	1.534
$t$ -statistic	3.52	6.58	8.13	9.84	14.58

Fifth Quintile: Largest Market Capitalization Stocks

	1st per	25th per	50th per	75th per	99th per
$b_1^*$ (in Cents/Share)	0.106	0.308	0.441	0.628	1.465
$b_1$ (in Cents/Share)	0.058	0.224	0.328	0.472	1.134
$t$ -statistic	4.21	8.29	10.52	12.38	24.71



Panel B

First Quintile: Smallest Market Capitalization Stocks

	1st per	25th per	50th per	75th per	99th per
$r^*$ (in %)	17.00	45.85	58.04	70.37	95.56
$r$ (in %)	5.92	37.57	51.15	65.30	94.44
$t$ -statistic	2.14	3.27	3.96	4.96	7.98

Second Quintile

	1st per	25th per	50th per	75th per	99th per
$r^*$ (in %)	21.04	47.78	59.08	70.28	94.62
$r$ (in %)	11.18	40.47	52.84	65.34	93.50
$t$ -statistic	2.57	3.97	4.72	5.54	8.95

Third Quintile

	1st per	25th per	50th per	75th per	99th per
$r^*$ (in %)	18.64	44.67	55.67	66.32	90.58
$r$ (in %)	11.92	38.04	49.63	61.13	88.93
$t$ -statistic	2.60	4.64	5.40	6.42	12.82

Fourth Quintile

	1st per	25th per	50th per	75th per	99th per
$r^*$ (in %)	20.45	42.10	51.11	59.81	81.61
$r$ (in %)	14.03	35.58	45.11	54.32	78.03
$t$ -statistic	3.44	5.66	7.05	8.18	12.86

Fifth Quintile: Largest Market Capitalization Stocks

	1st per	25th per	50th per	75th per	99th per
$r^*$ (in %)	18.68	39.38	47.42	55.20	74.82
$r$ (in %)	10.97	32.14	40.38	48.58	70.56
$t$ -statistic	4.43	7.71	9.70	11.83	24.22

**Table IV**  
**Summary Statistics for Intra-Day Parameter and AIM Estimates**

This table reports the parameter estimates' mean and standard deviation (std) for our 1,461 NYSE sample stocks. The regular hours are delineated into seven intra-day periods. For the first quarter in year 2003, observations of each stock are pooled according to these intra-day periods. The total number of observations for each time slot is  $N$ . Cross-sectional statistics are obtained and presented period by period. The coefficient of change in trade sign  $\Delta Q_i$  is denoted by  $C$ ; trade sign  $Q_i$  by  $b_1$ , signed volume  $X_i$  by  $b_2$ , signed duration  $Q_i \Delta T_i$  by  $b_3$  and duration  $\Delta T_i$  by  $b_4$  in the following equation for transaction price change  $\Delta P_i$ :

$$\Delta P_i = b_0 + C \Delta Q_i + b_1 Q_i + b_2 X_i + b_3 Q_i \Delta T_i + b_4 \Delta T_i + \epsilon_i .$$

$R_{asy}^2$  is the asymmetric information measure (AIM) obtained from the  $R^2$  value of the above equation and that of  $\Delta P_i = c_0 + c_1 \Delta Q_i + u_i$ .

		9:30 A.M. to 10 A.M.	10 A.M. to 11 A.M.	11 A.M. to 12 P.M.	12 P.M. to 1 P.M.	1 P.M. to 2 P.M.	2 P.M. to 3 P.M.	3 P.M. to 4 P.M.
Unit								
$N$ (mean)	Number	3,759	8,089	6,515	5,642	5,650	6,819	8,938
$N$ (std)	Number	4,121	8,436	7,160	6,320	6,244	7,249	8,636
$C$ (mean)	Cents/Share	0.59	0.58	0.58	0.59	0.58	0.56	0.56
$C$ (std)	Cents/Share	0.33	0.33	0.46	0.56	0.48	0.55	0.37
$t$ -statistic (mean)		18.8	30.0	29.5	28.4	28.9	31.6	34.0
$b_1$ (mean)	Cents/Share	1.06	0.86	0.77	0.73	0.71	0.68	0.64
$b_1$ (std)	Cents/Share	1.87	1.67	1.28	1.27	1.77	1.44	1.31
$t$ -statistic (mean)		11.5	16.8	15.4	14.3	14.2	15.3	16.0
$b_2 \times 10^3$ (mean)	Cents/Share	0.52	0.22	0.26	0.34	0.26	0.24	0.21
$b_2 \times 10^3$ (std)	Cents/Share	2.94	1.44	0.75	3.02	1.09	0.75	0.60
$t$ -statistic (mean)		2.50	2.97	2.96	3.32	2.92	2.99	3.57
$b_3 \times 10^3$ (mean)	Cents/Second	7.10	4.14	2.04	1.30	1.18	1.59	2.02
$b_3 \times 10^3$ (std)	Cents/Second	11.55	7.92	4.29	2.85	2.68	3.52	4.80
$t$ -statistic (mean)		3.91	4.33	2.86	2.16	2.02	2.42	2.47
$b_4 \times 10^3$ (mean)	Cents/Second	-0.25	-0.14	-0.12	-0.10	-0.09	-0.15	-0.13
$b_4 \times 10^3$ (std)	Cents/Second	2.01	1.07	0.75	0.59	0.60	0.69	0.84
$t$ -statistic (mean)		-0.31	-0.56	-0.45	-0.41	-0.44	-0.56	-0.48
$R_{asy}^2$ (mean)	%	20.54	17.57	16.59	16.30	16.02	15.83	14.65
$R_{asy}^2$ (std)	%	6.97	5.52	5.26	5.67	5.50	5.12	4.55

**Table V**  
**Summary and Test Statistics for Daily AIM around Earnings Announcements**

Panel A reports the statistics for ratios of average AIM estimates around earnings announcement dates over normal levels of informed trading, which are the average AIM estimates for other days. A ratio smaller (larger) than one is indicative that AIM is lower (higher) than the normal level. Three periods of two days each are considered: before, during and after an earnings announcement. Two days during an announcement are the announcement date itself and the following day. The three periods are non-overlapping. Median, mean and standard deviation (Std) statistics for 4,748 announcement dates in year 2003 for our NYSE sample are reported. Respectively, Upside and Downside refer to the positive and negative differences between actual earnings per share and analysts' consensus, while Met denotes that the actual earnings met analysts' expectation. The numbers of subsample observations for downside and upside surprises are 1,373 and 2,564, respectively. The remaining 811 quarterly earnings are in line with analysts' forecasts. Panel B reports the Wilcoxon signed rank tests'  $z$ -statistics ( $z$ -stat) and the two-population mean tests'  $t$ -statistics ( $t$ -stat). These tests are designed to ascertain whether the ratios are the same from one period to the other.

Panel A: Summary Statistics for Ratios

	Two Days Before				Two Days During				Two Days After			
	All	Downside	Met	Upside	All	Downside	Met	Upside	All	Downside	Met	Upside
Median	0.97	0.97	0.97	0.97	0.92	0.91	0.91	0.92	0.91	0.90	0.91	0.92
Mean	1.00	1.00	1.00	1.00	0.95	0.93	0.95	0.96	0.94	0.93	0.93	0.94
Std	0.26	0.28	0.27	0.25	0.24	0.24	0.22	0.25	0.25	0.26	0.25	0.24

Panel B: Test Statistics for Null Hypotheses of Same Ratios Across Periods

	During – Before				After – During				After – Before			
	All	Downside	Met	Upside	All	Downside	Met	Upside	All	Downside	Met	Upside
$z$ -stat	-10.92	-6.73	-4.63	-7.29	-3.09	-1.48	-1.72	-2.12	-13.68	-8.05	-6.12	-9.27
$t$ -stat	-9.93	-6.98	-4.66	-5.75	-2.43	-0.46	-1.01	-2.41	-12.20	-7.12	-5.28	-8.38

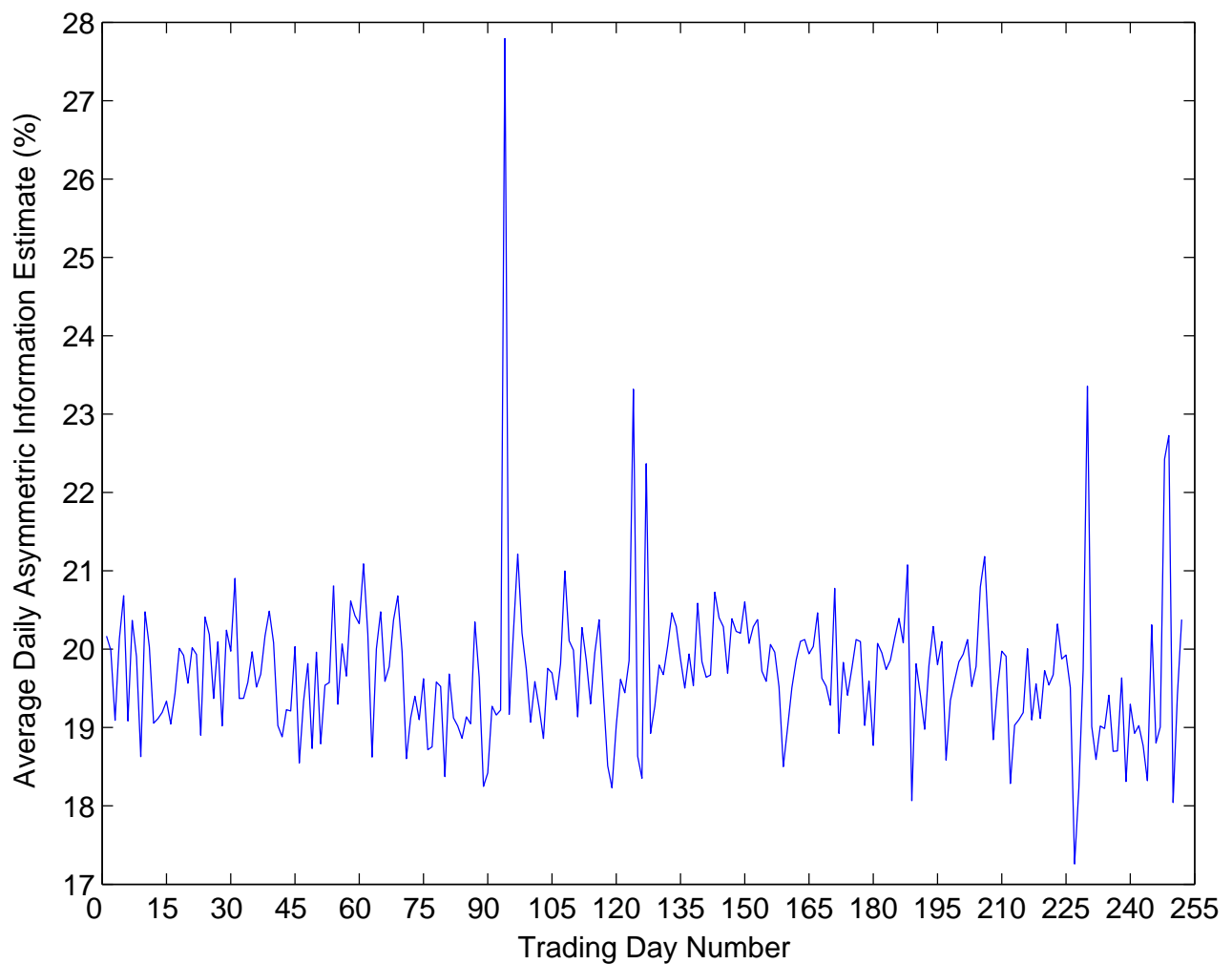
**Table VI**  
**AIM of a Firm and Information Structure**

This table reports the summary statistics for five cross-sectional regressions labeled as A, B, C, D and E. The dependent variable is the asymmetric information measure ( $AIM_j$ ) for a firm in year 2003. The number of sample stocks is not the same for these five regressions. This is because not all the firms in our sample have a record for the number of shareholders (Shareholders) in Compustat, and for the number of analysts following the firm (Analysts) in I/B/E/S. Information concerning the indicator variable Option is obtained from the Options Clearing Corporation. The  $t$ -statistics are shown in the parentheses. The adjusted  $R^2$  values in this table indicate the goodness of fit for these five regressions.

Regression	Intercept	Shareholders	Analysts	Option	Number of stocks	Adjusted $R^2$
A	21.9 (-96.1)	-1.06 (-13.7)			1,275	11.5%
B	28.9 (74.2)		-4.32 (-27.6)		1,279	45.2%
C	27.3 (79.0)	-0.55 (-8.65)		-8.68 (-22.0)	1,275	48.7%
D	29.5 (84.1)		-2.80 (-16.1)	-5.24 (-14.5)	1,279	56.2%
E	29.4 (81.2)	-0.28 (-4.80)	-2.59 (-14.4)	-5.08 (-14.0)	1,207	57.1%

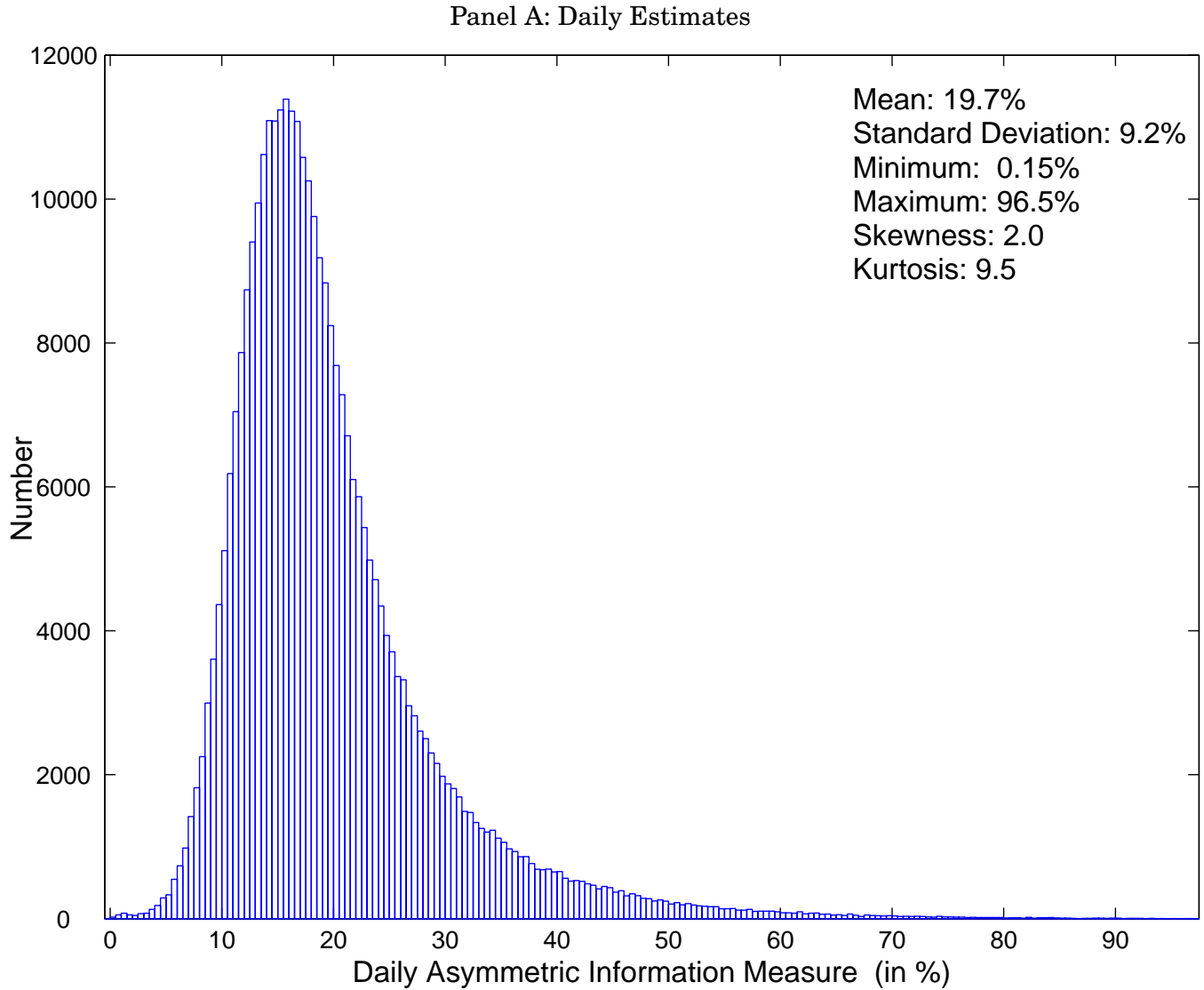
**Figure 1. Time Series of Cross-Sectional Daily Average Values.**

This figure plots the cross-sectional average value of AIM on a daily basis. This asymmetric information measure is the joint contribution of four variables in equation (5) in explaining intra-day price changes. These four variables are trade sign, signed volume, signed duration and duration. On each trading day in our sample period of year 2003, we estimate AIM for each sample stock. The daily average is taken cross-sectionally and plotted as time series.

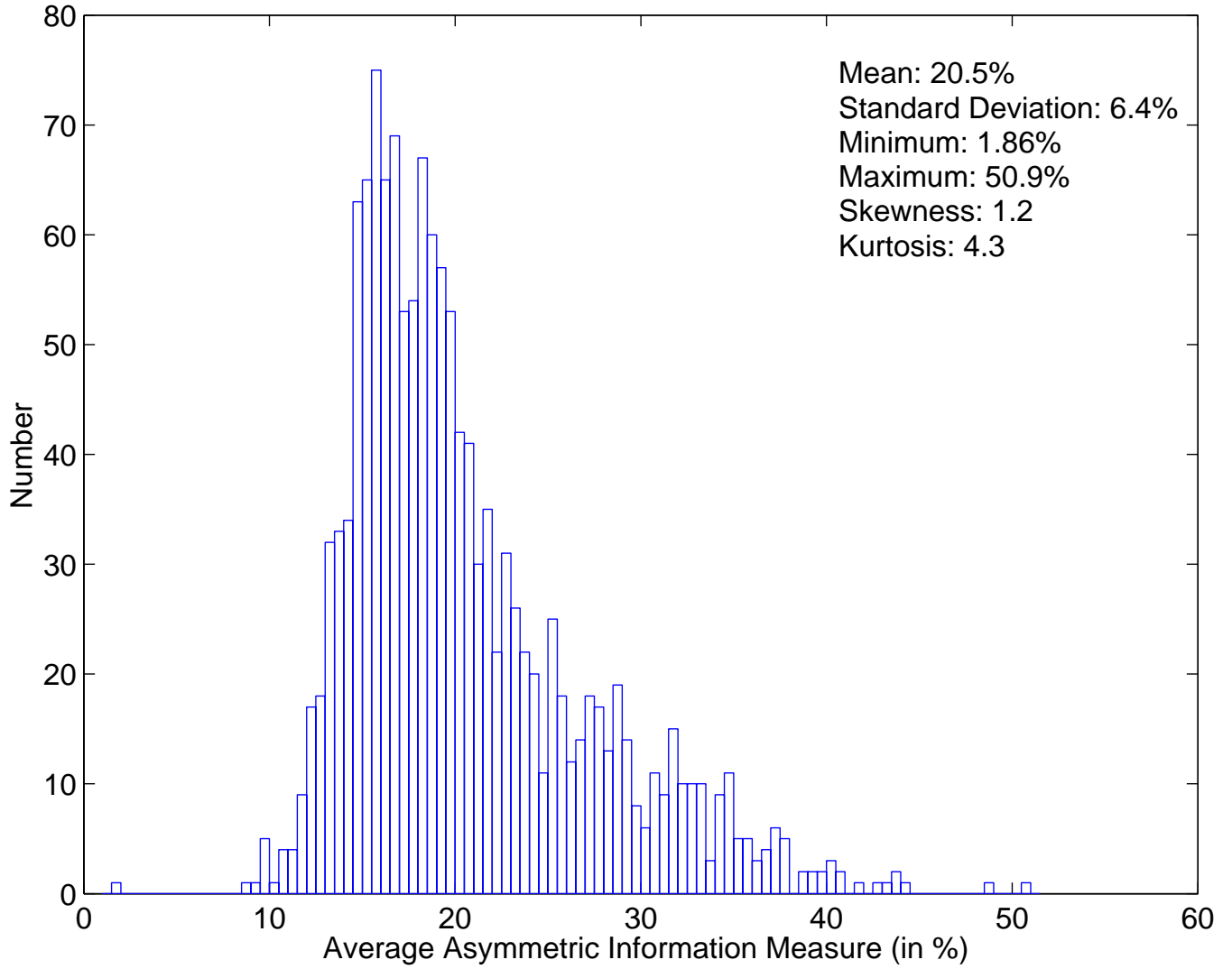


**Figure 2. Distributions of Asymmetric Information Estimates.**

This figure plots the histograms for the estimates of asymmetric information from high-frequency data. The asymmetric information measure is the joint contribution of four variables in equation (5) in explaining intra-day price changes. These four variables are trade sign, signed volume, signed duration and duration. Our sample comprises 1,461 NYSE common stocks and our sample period is year 2003 (252 trading days). In total, we have 329,187 stock-days. Panel A shows the histogram for this number of daily estimates. Panel B displays the histogram of 1,461 values averaged over the sample period.



Panel B: Daily Estimates Averaged Over the Sample Period



**Figure 3. Earnings Surprises and Informed Trading**

This figure plots three curves of average  $\alpha$  ratios for our NYSE sample stocks that have analysts following. The horizontal axis is the day number with Day 0 being the earnings announcement date. The  $\alpha$  ratio measures the level of informed trading relative to the normal level, which is the average AIM value for days not surrounding the earnings releases in year 2003. The normal level is a constant for a given stock. If AIM values for days near the announcement date is higher (lower) than the normal level, then the  $\alpha$  ratio is larger (smaller) than one.

