Earnings Announcement, Private Information, and Strategic Informed Trading

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Abstract

In this paper, we estimate and test a multi-period model of strategic informed trading, developed by Foster and Viswanathan (1996) via the Generalized Method of Moments, using prices and trading volumes during three hour period leading up to the earnings announcements made by NYSE firms. Among other things, it is shown that generalizing the model from a monopolistic informed trader to homogeneously informed multiple traders does not significantly improve the performance of the model. On the other hand, for some subsamples, generalizing the information from homogeneous to heterogeneous improves the performance of the model significantly. In addition, for some subsamples, the informed traders are shown to have slightly negatively correlated private signals near the announcements.

Key Words: Market Microstructure; Strategic Informed Trading; Earnings Announcements
JEL Classification: D82, C52, and G14

Introduction

This study investigates the performance of stylized market microstructure models for the periods leading up to earnings announcements. A typical market microstructure model would assume that there are informed traders[1] who trade with a market maker in the presence of liquidity traders. Since the informational content of a corporate event is at first known only to a small number of insiders and/or investors, a period leading up to a corporate event should be considered as an appropriate sample period for empirical analyses of these models.

Several market microstructure studies have attempted to analyze the implications on trading costs induced by possible informed trading during an event period. Most of these studies investigates the observable measures of liquidity such as spread or depth. For example, Morse Krinsky and Lee (1996) estimate the components of spread surrounding earnings announcements, and find that the adverse selection component of spread increases during both pre- and post-event periods. Lee, Mucklow and Ready (1993) examine both the spread and depth around earnings announcement and find that spreads widen and depth fall in anticipation of earnings

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[1] The models that study strategic informed trading can be categorized into three groups depending on the number of informed traders and their information structure. First, Kyle (1985) has a monopolistic informed trader. Second, Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) have multiple homogeneously informed traders. Lastly, Foster and Viswanathan (1996) have multiple traders with heterogeneous information.

announcements.[2] On a different track, Seppi (1992) builds a model of block trading near earnings announcements and finds that these trades reflect information contained in the upcoming earnings announcements. These papers collectively provide evidence that trades based on information occur prior to the announcements, and the liquidity providers reflect these anticipated adverse selection problems in their pricing function. In the present paper, it is the intertemporal patterns of price and trading volume prior to the earnings announcements that we use in order to examine the properties of private information.

This paper differs from the above mentioned studies in that we employ a structural model estimation which allows us to explicitly estimate the fundamental parameters of the theoretical model. The primary model that we estimate here is a model of speculative trading between a risk-neutral market maker and heterogeneously informed traders, developed by Foster and Viswanathan (1996). The informed traders not only compete each other for the trading profits, but also learn about the other traders' information from the past orders. Each trader is strategic in that he has long-lived private information and places orders to maximize his expected current *and* future profits. This model is a generalization of two simpler models: the Holden and Subrahmanyam (1992) model which has multiple traders but with homogeneous information, and the multi-period Kyle (1985) model which has a monopolistic informed trader. The Foster and Viswanathan (1996) model is the only one among the Kyle-variant models that can explain the empirically documented reduction in the market depth near the information resolution. Testing the simpler models against the general model will help us learn how restrictive the added assumptions are, providing clues as to the characteristics of private information in an environment where we believe that a certain degree of informed trading exists.

The structural estimation has numerous merits. Most importantly, it helps us gain insights into the fundamental sources of price-volume formation processes, and measure the relative importance of these sources. Even though structural estimation has merits, it also has drawbacks when it is applied to market microstructure models. The primary difficulty is the unobservability of the state variables. In other words, an econometrician can never observe private information nor liquidity trading. In this paper, we overcome this problem by deriving moment conditions on the observable price volatility and trading volume from the model's equilibrium restrictions, and then applying the Generalized Method of Moments (GMM) to estimate the models.

Recently, several structural estimations of market microstructure models have been successfully undertaken. Among others, Easley, Kiefer, O'Hara and Paperman (1996) estimate the probability of informed trading by working with the number of buys and sells during a trading day. They find that the probability of informed trading is lower for high-volume stocks.

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[2] Morse and Ushman (1983) and Venkatesh and Chiang (1986) investigate the changes in the spread near earnings and dividend announcements. Both studies document that spread increases at least on the day of announcement.

Easley, Kiefer and O'Hara (1997) include number of no-trades. Also, Foster and Viswanathan (1995) test if the stylized facts about the relation between trading volume and price volatility can be explained by a market microstructure model in which the information is modeled as a latent variable. They impose a specific structure on the information process and reject the model. Cho and Krishnan (1999) utilize the fact that true value of a futures contract is known ex-post, and estimate the Hellwig's noisy rational expectations equilibrium model by using the S&P 500 futures contracts. They find that in the index futures market the main source of uncertainty is liquidity trading rather than the diversity of private signals. Caballé and Krishnan (1995) estimate a model with multiple securities and short-lived information. They establish moment restrictions on prices and order flows, and estimate the model using the GMM and maximum-likelihood estimation. An important contribution of the present paper is that a model of strategic trading with long-lived information is specifically applied to an event, i.e., earnings announcements, thereby addressing the issues related to strategic informed trading.

Accordingly, this paper purports to answer questions like the following: (i) Is there informed trading near earnings announcements?, (ii) How restrictive are the assumptions of multiple informed traders with homogeneous information, and monopolistic informed trader?, (iii) How correlated are the private signals?, (iv) How much of the trading is done by the informed traders, liquidity traders and the market maker?, and (v) How much of the price innovations is initiated by informed trading, and by liquidity trading?

The major findings are (i) there is evidence of informed trading during the preannouncement period, (ii) three hours prior to the earnings announcements, the informed traders have heterogeneous and negatively correlated private signals, (iii) generalizing the model from a monopolistic informed trader to homogeneously informed multiple traders does not significantly improve the performance of the model, whereas generalizing the information from homogeneous to heterogeneous improves the performance of the model significantly, and (iv) the contribution of informed trading to both price volatility and trading volume increases as time approaches the announcement.

The rest of the paper is organized as follows. Section I introduces the models with the moment restrictions to be used for the GMM. In Section II, the description on the data together with normalization process is given. In Section III, model estimation and testing strategies are discussed. In Section IV, empirical findings are presented. Section V concludes with a summary.

I. Models

In this section, we introduce the models to be estimated. First, we will reproduce the model developed by Foster and Viswanathan (1996) [hereafter FV] which will serve as the unrestricted model for this paper. This model can be viewed as the most general model among

the models that originate from Kyle's (1985) multi-period model[3]. In FV, there are multiple informed traders who are heterogeneously informed. The heterogeneity of information is modeled by assuming that the informed traders receive correlated signals about the terminal value of the asset. The informed traders are strategic in that they compete with each other for profits that they expect to make not only from the current trading but also from the future trading. In addition, the informed traders learn about the other traders' private signals by observing the history of orders.

There are two models that will be tested against FV. These models are restricted models in that they are nested in FV. By restricting the correlation that characterizes the heterogeneity of private information to one, FV reduces to a model with homogeneously informed multiple traders. The models by Holden and Subrahmanyam (1992) [hereafter HS] and Foster and Viswanathan (1993) fall in this category. If we further assume that there is only one informed trader, FV reduces to the Kyle model. In what follows, a brief description of the models together with the moment restrictions on price volatility and trading volume implied by these models will be provided.

I.1 Description of the models

In FV, there are three types of risk-neutral traders; a market maker, M informed traders and a number of liquidity traders. There are T trading periods with the following time line of events. Both the market maker and the informed traders initially share common priors about the distribution of the liquidating value of the asset. Before the trading starts, i.e. at time 0, information about the mean of the distribution is revealed to the informed traders. Each trader receives a private signal that is correlated to, but may well be different from the others'. In the context of our empirical analysis, this signal can be viewed as private information regarding the upcoming earnings announcement.

Once the trading starts, four events occur during each trading period t, for $t = 1, \ldots, T$.[4] First, each informed trader updates his valuation of the asset by observing the previous period's orders. By doing so, the informed traders learn about the other traders' information which is partially revealed in the past orders. Second, the informed traders submit orders that represent the changes in their demand. They act strategically in that when submitting their orders, they

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[3] Cho (1995), Holden and Subrahmanyam (1992), and Foster and Viswanathan (1992, 1996) develop Kyle-variant models similar to the present model. Cho (1995) assumes that the private information evolves during the trading periods, while the others assume multiple informed traders.

[4] In the empirical analysis, we use the price changes and trading volumes leading up to earnings announcements in 30-minute intervals. Each trading period, therefore, can be interpreted as a 30-minute interval.

attempt to maximize the expected sum of *current and future* profits.[5] Third, the liquidity traders arrive at the market and submit their orders. The market maker observes only the net order, which is a sum of the orders from the informed trader and the liquidity traders. Finally, the market maker sets the price so that it is equal to the expected liquidating value of the asset, and the market clears at this price.[6]

The exogenous parameters of the model that we estimate are the number of the informed traders, *M*, the initial informativeness of price, Σ_0[7], the parameter that characterizes the correlation between individual signals, χ, and the amount of liquidity trading, σ_u.[8] Given the values of these exogenous parameters, all the other endogenous parameters, such as the parameters that characterize liquidity, λ, and trading aggressiveness, β, are completely specified. Proposition 1 in Foster and Viswanathan (1996) shows the recursive linear Markov equilibrium that characterizes the endogenous parameters as functions of the exogenous parameters.

The exogenous parameters, χ, and *M* play an important role in relating the FV model to HS and Kyle. The parameter, χ, is defined to be the difference between the conditional variance of each private signal, Λ_t, and the conditional covariance between two private signals, Ω_t, i.e. $\chi = \Lambda_t - \Omega_t$.[9] Therefore, since $\chi = 0$ implies perfect correlation between two signals, the FV model becomes HS if χ is restricted to 0. Furthermore, when *M* is restricted to 1, the model becomes Kyle, since the Kyle model assumes a monopolistic informed trader.

I.2 Moment restrictions on price volatility and trading volume

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5 Notice, however, that an informed trader with short-lived information, as in Admati and Pfleiderer (1988), Hughson (1990) and Caballé and Krishnan (1995) will not act strategically, since he will maximize only the current expected profits. This means that an informed trader perceives no benefit in limiting the resolution of his information for future profits. The informed trader in the present model may trade less aggressively than a nonstrategic informed trader, especially early in the trading periods, to obtain larger *overall* profits.

6 Interested readers should consult the original paper for more detailed description of the equilibrium.

7 In FV, Σ_0 is the conditional variance of the *sum* of the private signals. In the present paper, however, we define Σ_0 to be the conditional variance of the *average* of the private signals. In other words, we need to multiply Σ_0 in the present paper by M^2 in order to obtain Σ_0 in FV. This will not present any problem, since both the sum and the average are a sufficient statistic for the liquidating value of the asset. This re-scaling will help us aligning the meaning of Σ_0 across all the models that we estimate.

8 In the original model, there is another exogenous parameter: the initial prior. In the empirical part, instead of estimating the parameter, we substitute the prevailing price at the beginning of the trading periods for the initial prior.

9 One of the properties of FV is that χ is constant for all *t*.

In this sub-section, we present a series of propositions that summarize the moment restrictions on price volatility and trading volume implied by each of the above mentioned three models. These conditional moments will serve as the orthogonality conditions in the GMM procedure. First, the following proposition shows the conditional means of price volatility and trading volume implied in Foster and Viswanathan (1996).

Proposition 1 (FV: General Model) *Given the history of prices, the conditional means of price volatility and trading volume for t = 1,2, … ,T are*

(1) $$E(\Delta p_t^2 \mid p_1,\ldots,p_{t-1}) = M\lambda_t^2\beta_t^2\Lambda_{t-1} + M(M-1)\lambda_t^2\beta_t^2\Omega_{t-1} + \lambda_t^2\sigma_u^2,$$

(2) $$E(TV_t \mid p_1,\ldots,p_{t-1}) = \sqrt{\tfrac{1}{2\pi}}\left(M\sqrt{\beta_t^2\Lambda_{t-1}} + \sqrt{\sigma_u^2} + +\sqrt{M\beta_t^2\Lambda_{t-1} + M(M-1)\beta_t^2\Omega_{t-1} + \sigma_u^2}\right).$$

(*proof in Appendix* 1)

The expected price changes given in (1) have three terms. They measure respectively, the amount of price change attributable to (i) the degree of residual privateness of each informed trader's private information, (ii) the learning by the informed traders about other informed traders' information, and (iii) the liquidity trading.

In order to obtain the conditional expectation of trading volume in (2) we need to first define the trading volume. As in Admati and Pfleiderer (1988), there are three contributors to trading volume: the informed traders, liquidity traders and the market maker. We define the trading volume to be one half of the sum of absolute values of orders submitted or received by the above market participants. For example, suppose that two informed traders want to buy 5 and 3 shares and the liquidity traders want to sell 6 shares. Then, the market maker observes the net order to buy 2 shares. The market maker sets an equilibrium price and absorbs the order. In this example, the total trading volume will be 8 shares, which is precisely one half of (5+3)+6+2. The case when both the informed trader and the liquidity traders submit orders in the same direction can be worked out similarly. In (2) the first term represents the trading volume generated by the informed traders, the second term, by liquidity traders, and the last term, by the market maker. One of the primary advantages of a structural model estimation is that once estimation is done, we can explicitly quantify the relative importance of the sources that determine the price innovation and trading volume. This will be done in the subsequent sections.

Recall thatby restricting some parameter vlaues, we obtain either HS or Kyle. In the following propositions, we derive the conditional means of price volatility and trading volume implied by HS and Kyle.

Proposition 3 (HS: Homogeneous Private Information) *If = 0, i.e. the informed traders receive homogeneous private signals, then*

and (3)

(4)

Proposition 4 (Kyle: Monopolistic Informed Trader) *If there is only one informed trader who receives private information, then*

and (5)

(6)

with $_t = {}_t = {}_t = M = 1$ *for* $t = 1,2,..,T$.

When there is a monopolistic informed trader as in Kyle, market depth measured by the inverse of the market maker's pricing parameter, , stays constant for most of the trading period, but increases right before the revelation of liquidating value of the underlying asset. On the other hand, when there is more than one informed trader as in HS , the increase in market depth occurs early in the trading period and stays constant for the remaining period. Neither of these models, however, can yield a market depth pattern that exhibits a reduction near the information resolution. In FV, however, depending on the correlation structure of the agents' private signals and the number of trading periods involved, a reduction in the market depth near the end of trading period can be obtained.

A commonality in these three models is that each informed trader acts strategically, yielding specific patterns in price volatility and trading volume, depending on the level of correlation in their private signals and number of trading opportunities. For example, when the private signals are identical, i.e., perfect correlation, if there is more than one informed trader, there will be a rat race among the informed traders, and the trading volume and the price volatility will be the highest at the beginning of the trading period. On the other hand, if the informed trader is monopolistic, or the informed traders' private signals are loosely correlated, there will be a gradual revelation of private information, and trading volume and price volatility will peak near the end of the trading period.

It is, therefore, interesting to see empirically how restrictive the assumption of strategic trading is. To examine this, we compare these models with a model where there is no private information, EFF. In EFF, price changes purely due to public information and trading occurs only to accommodate liquidity motivated orders. This model will also be used to investigate the empirical importance of matching the timing of information resolution in theoretical models with actual announcements. The conditional expectations of price volatility and trading volume implied by EFF are shown in the following proposition.

Proposition 5 (EFF: Model with Pure Public Information) *If there is no privately informed trader, then*

and (I.36)

, *for all* $t = 1,..., T$, (I.37)

where $_p^2$ *is a constant that measures the amount of public information that leads to price changes from one period to the next.*

This model can be interpreted as a model which depicts an informationally strong form efficient market. In this model, prices are a white noise. Also, trading volume is driven by the liquidity traders, and all the orders are absorbed by the market maker without changing prices. Unfortunately, EFF and the models of strategic informed trading are not nested in each other. As a results, a classical hypothesis testing cannot be done. Instead, a *pseudo* test statistic is provided as a yardstick for comparing one's restrictiveness to the other's.

II. Data

The sample moments of price volatility and trading volume are constructed from the prices and trading volumes leading up to quarterly earnings announcements made by NYSE firms from January 1, 1991 to March 31, 1991. The announcement data are obtained from the PR Newswire data base, where each announcement is time-stamped to the nearest minute. In order to determine the *de facto* announcement dates based on when the information is actually reflected in stock prices, we assume that any announcement that was made after 3:30 pm EST was made on the following trading day. This is implemented under the presumption that it should take some time for the market to respond to an announcement.[10] Once an announcement date is determined, we obtain return and trading volume series from the Center for Research in Security Prices (CRSP) data base to calculate 10 daily price volatilities and trading volumes leading up to and inclusive of the announcement date. In all, there were 955 earnings announcements in the original PR Newswire data base. The final number of announcements that are used in this paper is 824. Announcements were dropped for several reasons. First, if multiple announcements were recorded on the same day for an identical company, all duplicate records were dropped. Second, if two separate announcements were made within a two calendar week interval, the later one was dropped. Last, if a stock split within two weeks prior to the announcement, if there was any missing return or trading volume within two weeks prior to the

[10] There were 13 announcement that were made between 3:30 pm and the market closing, 4:00 pm. This represents less than 2% of the total sample.

announcement, or if a company name in the PR Newswire data base was not found in the CRSP data base, the announcement was dropped.

Note that the moment restrictions given in the preceding section are in terms of prices rather than returns. This gives rise to a necessity to normalize the price and volume series, since each firm has a different level of stock price. The normalization is done as follows. For the sake of simplicity, let '0 day' be the earnings announcement day. Then, we denote the value of a '*variable*' as of *t* days prior to the earnings announcement as -*t* day '*variable*'. For example, the stock price 5 days prior to the announcement will be called '-5 day stock price'.

Now, as to the normalized price, we first set the -10 day stock price to be 100.[11] Then, we take the return series from -9 days and generate the index stock prices. For example, if the -10 day return of a stock were 1%, the -9 day stock price will be 101. We use return series rather than the price series, since the returns in the CRSP data base reflect the value of the stock better than the price series in that only the returns take other payments such as dividends into account. Once all the normalized prices are calculated, for each announcement, we calculate the price volatilities by taking the square of the difference between adjacent normalized prices.

Normalizing trading volume is not as straightforward as normalizing prices. The complexity arises from the fact that we need to use normalized volumes with the normalized prices. In other words, we need to normalize the trading volume in such a way that the normalized volume would represent the correct trading volume when it is used with a normalized price. In order to achieve this, we first ask what would be the -10 day number of shares outstanding if the -10 day stock price were 100. And then, we evaluate the normalized trading volume based on this hypothetical number of shares. Specifically, first, we calculate -10 day 'unit trading volume'.[12] The unit trading volume measures the hypothetical trading volume if -10 day stock price and the trading volume were 100 and 1, respectively. This can be obtained by dividing -10 day stock price by 100. Once the unit trading volume is calculated, we then obtain the normalized trading volume by multiplying the actual trading volume by the unit trading volume. For example, suppose an actual -10 day stock price and trading volume were 50 and 100 respectively and -9 day price and trading volume, 55 and 300 shares. Then, -10 day and -9 day normalized trading volumes would be 0.5(100) = 50, and 0.5(300) = 150 shares. Notice that regardless of the change in price, this procedure preserves the fact that -9 day trading volume is 3 times as large as -10 day trading volume.

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[11] One of the benefits of setting the initial price at 100 is that once all the parameters and measures related to price changes are estimated, these can be interpreted as percentages of prices.

[12] The primary reason for working with the unit trading volume is to fix the equity base as of the benchmark date, i.e. 10 days prior to the earnings announcement. If we do not fix the equity base and normalize as we would with the prices, we will end up with some measure which is analogous to total value of traded stocks.

After we obtain the normalized price and volume series, we group the whole sample into three subsamples according to the firm's -10 day market capitalization. As a result, in the large firm sample, there are 274 announcements, and in the medium and small firm samples, 275 each. Table 1 shows the summary statistics of the data.

Please Insert Table 1 approximately here.

A notable observation one can make from Table 1 is that the prices are, in general, declining as time approaches the announcement.[13] Also, the price volatility and trading volume are peaking as time approaches the announcement date. This casual empiricism seems to offer evidence of strategic informed traders endowed with less than perfectly correlated private signals, who trade and learn with their fore-knowledge of negative news contained in the announcements. In the subsequent sections we will investigate this claim more in detail.

III. Estimation and Test Methodology

The estimation methodology employed in this paper is the Generalized Method of Moments (GMM). Recall that the FV, HS, Kyle and EFF models are represented by their implications on the interday expected price volatility and trading volume. Even though the models' state variables, i.e. private signals and liquidity trading, are all unobservable, since the equilibria are expressed in observable price volatility and trading volume, the models can be estimated.

In actual estimation, we estimate the models for two different time horizons, for 5 and 10 trading days leading up to and including announcement dates. When a model is estimated with the 5 (10) day trading horizon, there are 10 (20) moment restrictions: 5 (10) on the price volatilities and the other 5 (10) on the trading volumes. In order to apply the GMM, we first obtain the sample moments by evaluating from each sample, the cross-sectional averages of inter-day normalized price volatility and trading volume. Then, using the equations (I.30)-(I.37) as theoretical moments, we find a GMM estimator which minimizes the distance between the theoretical moments and the sample moments, in which the distance is measured with respect to a weighting matrix. In order to work with an optimal weighting matrix, a standard two-stage GMM methodology is performed. The first stage uses an identity matrix as a weighting matrix. Once the first-stage estimation is done, we re-estimate the models using the optimal consistent weighting matrix which incorporates the Newey and West (1987) correction for heteroskedasticity and serial correlation.

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13 During this period the S&P 500 index gained about 13%.

More formally, let z be the $(2T\times 1)$ vector of sample moments, where T is either 5 or 10. Given a set of parameter values of the number of informed traders, M, the covariance between any two signals, $_0$, the difference between initial variance and covariance of the signals, ,[14] and the amount of liquidity trading, $_u{}^2$, we evaluate the $(2T\times 1)$ vector of theoretical moments, $h(\ )$, where $(M,\ _0,\ ,\ _u{}^2)$.[15] Even though the number of informed traders is an integer, in order to facilitate the estimation, we treat it as if it were a real number in the estimation part. This change does not affect the economic intuition about the interpretation of the equilibrium given in Proposition 1.[16] Now, let $g(\ )\quad z - h(\ )$. Then for an optimal weighting matrix
, a GMM estimator
minimizes the following criterion function:[17]

. (III.1)

In order to test the models, we estimate both the general and the restricted models and evaluate Distance Metric statistics (*DM*) as suggested in Newey and McFadden (1994).[18] If
is the GMM estimator for the general model and
is for a restricted model, the *DM* statistic can be calculated by

, (III.2)

where n is the number of observations[19] and $Q(\ )$'s are the minimized values of the criterion function evaluated at the respective GMM estimates. Since HS assumes a perfect correlation among private signals, we can test HS with the null hypothesis that =0, and under the null hypothesis the *DM* statistic converges to a chi-square with one degree of freedom. In addition, Kyle assumes that the number of informed trader is 1. In Kyle, therefore, the pertinent null hypothesis is =0 and M = 1, and under the null hypothesis the *DM* statistic converges to a chi-square with two degrees of freedom. In contrast, because EFF is not nested in FV, we do not

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14 Recall that as noted in (I.7), the difference between conditional variance and covariance of the private signals is constant. Therefore, by estimating any two of $_0$, $_0$ and , we can identify all three parameters. In what follows, we estimate $_0$ and .

15 In order to estimate the model, we need to have the unconditional mean of the asset, p_0. In the estimation we let the previous day's closing price (-10 day closing price) be the unconditional mean.

16 Foster an Viswanathan (1995) also estimate the model assuming that the number of informed traders is a real number.

17 We use a constrained minimization where M is constrained to be larger than 1 and , larger than 0.

18 This statistic is analogous to the Likelihood Ratio statistic in Maximum Likelihood Estimation.

19 There are 824 observations in the whole sample, 274 in the large firm sample, 275 in medium and small firm samples.

know the limiting distribution of the *DM* statistic. However, since this statistic can be interpreted as comparing the goodness of fit between the two models, we evaluate the statistic and refer to it as a *pseudo-DM* statistic as a point of reference.

IV. Empirical Results

=> Sig_0 needs to be divided by M^2 in the FV model.

IV.1 Parameter Estimates

In Table 2, the parameter estimates of FV are reported for 10-day and 5-day trading horizons with the whole sample, and the samples of large, medium and small firms. This table also reports the variance of private signals, $_0$, and the correlation of any two private signals, $_0$, which are functions of the parameters that are estimated. By (I.7) $_0$ is calculated by adding $_0$ and , while $_0$ is calculated by diving $_0$ by $_0$.

Please Insert Table 2 approximately here.

First, the results show that the variance of private signals, $_0$, decreases with firm size for both the two trading horizons. For example, with the 10-day trading horizon, $_0$ is 28.49 for the large firms, 44.43, for the medium sized firms, and 63.69, for the small firms. In terms of standard deviation, since the initial prices are normalized at 100, ($_0$)½ is 5.34%, 6.67% and 7.98% respectively. This is in line with the other empirical findings such as Easley *et al.* (1996) that the smaller firms have a higher degree of informational asymmetry. Even though is not well identified for the 5-day trading horizon, the general level of the informational asymmetry is reduced as time approaches the announcement. For example, with the whole sample, the variance of private signal decreases from 41.74 to 36.84. This suggests that the information contained in the upcoming earnings announcement is gradually being revealed to the market participants. What is interesting is the cross-sectional difference in the reduction of informational asymmetry. For the small firm sample, the reduction is by only about 5% (from 63.69 to 60.69), while those for the large and medium-sized firms are by 29% and 42% respectively. This may suggest that for smaller firms, informed traders acquire their private information relatively later than for the larger firms.

Second, the correlation between the private signals, in general, increases as time approaches the announcement. With the whole sample, the correlation coefficient increases from 0.05 to 0.68. This suggests that overall the traders learn about the other traders' signals. In

particular, with the large firm sample, the correlation changes from 0.05 to 1.00. This suggests that by the start of the last week prior to the announcement, the informed traders are practically in agreement with the information contained in the upcoming announcement. This can be attributable to active learning by the informed traders during the former half of 10-day trading period. With the small firm sample, however, the correlation increases from 0.01 to 0.69, implying that with the smaller firms, the information received by the informed traders is yet to be homogenized by a week before the announcement.

Third, the parameter estimates of the number of informed traders have large standard deviation and thus are not well identified. The <> under the parameter estimate shows the z-statistic to test the hypothesis that *M* is larger than 1. This hypothesis is not rejected for any specification.[20]

Lastly, the larger the firm gets, the heavier the liquidity trading becomes. Interestingly, there is little change in the level of liquidity trading from for 10-day trading horizon to 5-day horizon. This suggests that if liquidity trading is measured over a week interval it does not increase nor decrease as announcement approaches.

IV.2 Test of Models

IV.2.1 Heterogeneous *vs.* Homogeneous Information

In this section, we investigate the restrictiveness of the assumptions of homogeneous information and monopolistic informed trader. Recall that the HS model is derived from FV by assuming that the informed traders receive homogeneous information, while Kyle is derived by further assuming that the informed trader is monopolistic. The test results are reported in Table 3.

Please Insert Table 3 approximately here.

Panel A and Panel B in Table 3 show the *DM* statistics when the model is applied to 10-day and 5-day trading horizons respectively. First of all, in conjunction with the parameter estimates of the correlation among private signals, the results attest to the fact that as time nears announcement, the degree of heterogeneity in private signals decreases, possibly due to the

[20] It will be shown, however, that if we restrict the model to have a monopolistic informed trader (Kyle model), the model is rejected against the current model (FV model) for some samples. The source of rejection, therefore, seems to arise not from the number of informed traders in the market, but from the assumption of homogeneity of private signals.

learning by the informed traders about the other traders' signals. This can be seen by the decrease in the *DM* statistics from 5-day trading horizon ton 10-day horizon for all the samples.

Second, the models of homogeneous information are rejected against that of heterogeneous information for 10-day trading horizon with the whole and small firm samples. This suggests that with small firms, not only the general level of adverse selection problem is higher, but also the level of disagreement among the informed traders is higher. This may arise from the fact that the informational content of the announcement for the small firms is not yet available as of 10 days to the announcement. Notice that with 5-day trading horizon, the models of homogeneous information are not rejected for any of the samples. This suggests that as of 5 days to announcements, informed traders are in general agreement about the informational content of the upcoming announcement.

Third, the added theoretical restriction of monopolistic informed trader on to homogeneous private signals does not seem to impose further empirical restriction. As it can be seen, the *DM* statistics for HS and Kyle are identical up to 100th decimal points across all the samples and trading horizons. This means that if we test Kyle against HS, Kyle would not be rejected for all the cases. Therefore, it is moving from homogeneous information to heterogeneous information what really matters empirically, and not moving from a monopolistic informed trader to homogeneously informed multiple traders. The primary reason for this seems to arise from the fact that in our samples a rat race among the informed traders at the beginning of trading periods does not exist. Therefore, restricting the number of traders to one does not prove to be of any empirical significance.

IV.2.2 Existence of Strategic Informed Trading and Timing of Information Resolution

In order to see the restrictiveness of the assumption of strategic trading relative to that of informationally strong form efficient market, we compare FV to EFF. This question is related to the existence of informed trading near the earnings announcements. Krinsky and Lee (1995) document that the adverse selection component of bid-ask spread increases near the earning announcement. Kavajecz (1995) shows that the specialists use quoted depths strategically to minimize the adverse selection problem around an information event. The approach taken here is by directly comparing a model with private information to one without private information. The first column of Table 4 shows the results.

Please Insert Table 4 approximately here.

Table 4 reports which measures the difference of goodness of fit between FV and EFF. A positive *pseudo-DM* statistics signifies that FV fits the data better than EFF, and *vice versa*. In the first column we report the statistics when FV and EFF are estimated for 5-day trading horizon using the correct announcement dates. In this case, the *pseudo-DM* statistics range from about 4 to 24. This suggests that the restriction of strategic trading is less restrictive than the restriction of informationally strong form efficient market. In other words, the patterns in price volatility and trading volume are more likely to be generated from a model of strategic informed trading. This suggests that there is a strategic informed trading near the earnings announcements.

In the second column of Table 4, we report the *pseudo-DM* statistics when FV and EFF are estimated for 5-day trading horizon, assuming that the announcements were made a week prior to the actual announcement. This is done to study the empirical importance of matching the theoretical timing of information resolution to the actual timing.[21] In the theoretical market microstructure literature, the frequency and timing of information resolution vary. For example, at one extreme, Admati and Pfleiderer (1988) assume that the information is resolved after every round of trading. The restrictiveness of an assumption like this has never been studied empirically before. If matching the theoretical timing of information resolution with the actual timing is empirically important, the fitness of FV with false announcement dates should deteriorate from that with actual announcement dates, when compared with EFF. This is confirmed with the data.

If we impose false announcement dates, for all samples, the *pseudo-DM* statistics dramatically decrease to around -2 to -35. The sharp decrease in *pseudo-DM* statistics indicates that by forcing a false timing for information resolution, the model of strategic informed trading becomes less effective. Thus, when applying empirically a model of strategic informed trading, one should be very careful to correctly establish the timing of information resolution.

IV.3 Decomposition of Price Volatility and Trading Volume

One of the benefits obtained from structural model estimation is the possibility of not only identifying the underlying sources that bring about changes to observable variables, but also quantifying the respective source's relative contributions to the changes in observable variables. In this section, we document the relative contributions of the exogenous parameters to the price volatility and the expected trading volume. First, from the point estimates of FV with the whole sample for 10-day trading horizon, the expected price volatility and trading volume are estimated.[22] Then, using (I.30), we quantify in percentage terms, the contributions of informed

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21 This approach resembles the one taken by Kothari and Warner (1996).

22 These figures do not vary much cross-sectionally. An interesting pattern, even though it does not seem to be statistically significant, is that as time approaches the announcement, the proportion of informed trading increases the most with the large firm sample, the second with the medium firm sample,

trading and liquidity trading to the expected price volatility. Also, using (I.31), we quantify the relative contributions of informed traders, liquidity traders and the market maker to the expected trading volume.

Please Insert Figure 1 approximately here.

In Figure 1, the interday contributions of informed trading to expected price volatility for the whole is plotted. First, the proportion of the informed trading is less than that of the liquidity traders for all period. Initially, the contribution of the informed trading to the price volatility is less than 10%. Even when it is the largest, i.e., right before the announcement, it is less than 43%. This means that even when the market awaits an informational event, the proportion of informed trading to price innovation is fairly limited. Second, the proportion of informed trading increases as time approaches the announcement. This is not surprising in that the trading by informed traders would become more intensive as time approaches the announcement.

Please Insert Figure 5 approximately here.

In Figure 2, we show the interday composition of expected trading volume evaluated at the parameter estimates for the whole sample. There are two distinct features regarding the interday compositions of expected trading volume. First, as was the case with price volatility, the contribution made by the informed trader becomes larger as time approaches announcements. Again, this is due to the fact that the informed trader trades more aggressively as the announcement nears. Second, the proportion of market maker's trading volume is around 40% throughout, albeit decreasing slightly over time. What this means is that the net orders to be filled by the market maker are expected to increase in number of shares, but to be steady in the percentage of total trading volume. In other words, in equilibrium, since the liquidity traders' trading activity is assumed to be steady, the increased demand by the informed trader will mainly be filled by the market maker.

V. Conclusion

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and the least with the small firm sample. In other words, even though the adverse selection problem is the highest with the smaller firms, the informed traders cannot trade as aggressively as they would do with the larger firms. This seems to result from the market maker's pricing rule by which the trading costs implicit in market liquidity are the highest with the small firms.

In this paper, we estimate a theoretical model of strategic trading developed by Foster and Viswanathan (FV, 1996), where multiple informed traders receive heterogeneous private signals about an upcoming earnings announcement. This model nests two simpler models: (i) Holden and Subrahmanyam (HS, 1992) in which multiple informed traders receive homogeneous private signals and (ii) Kyle (1985) in which the informed trader is monopolistic. Once the equilibria of these models are solved, we derive the moment restrictions on the observable price volatility and trading volume. We then estimate and test the models with the Generalized Method of Moments (GMM) using the pre-earnings announcement price volatility and trading volume.

The major findings are, (i) there is evidence of informed trading during the preannouncement period with the adverse selection problems more severe with smaller firms, (ii) both the liquidity trading and the informed trading are more active for larger firms, (iii) for the small firm sample, the models of homogeneous information is rejected by the model of heterogeneous information, (iv) generalizing the model from a monopolistic informed trader to homogeneously informed multiple traders does not significantly improve the performance of the model, (v) mis-matching the timing of information resolution of the theoretical model with the actual announcement renders the empirical performance of the model less effective, and (vi) the contribution of informed trading to both price volatility and trading volume increases as time approaches the announcement.

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Appendix 1 : Proof of Proposition 1

In the interests of parsimony, we use the variables, parameters and equations as defined in Foster and Viswanathan (1996) without redefining them here. First, we prove (1). From equation (18), $\Delta p_t^2 = (p_t - p_{t-1})^2 = \lambda_t^2 \Delta y_t^2$, where y_t is the net order. Also, since the price changes and the net order flows are linearly related, a price change fully reveals the net order flow. Therefore, since the net order is the sum of orders from the informed traders and the liquidity traders,

(A.1) $$E(\Delta p_t^2 \mid p_1,..., p_{t-1}) = E\left\{ \lambda_t^2 \left(\sum_{i=1}^{M} x_{it}^2 + u_t^2 + 2\sum\sum_{i \neq j} x_{it} x_{jt} \right) \mid p_1,..., p_{t-1} \right\}.$$

Now, then, from equation (8),

(A.2) $$E(x_{it} x_{jt} \mid p_1,..., p_{t-1}) = E\left(\beta_t^2 s_{it-1} s_{jt-1} \mid p_1,..., p_{t-1}\right) = E\left\{\beta_t^2 s_{it-1} E(s_{jt-1} \mid s_{it-1}) \mid p_1,..., p_{t-1}\right\},$$

where s is the private signal, and the last equation is derived by using the law of iterative expectations. Then, by using the definition of ϕ_t given in Proposition 1 in Foster and Viswanathan (1996), we get

(A.3) $$E\left\{\beta_t^2 s_{it-1} E(s_{jt-1} \mid s_{it-1}) \mid p_1,..., p_{t-1}\right\} = \beta_t^2 E\left(\phi_t s_{it-1}^2 \mid p_1,..., p_{t-1}\right) = \beta_t^2 \phi_t \Lambda_{t-1} = \beta_t^2 \Omega_{t-1}.$$

Finally,

(A.4) $$E\left(x_{it}^2 \mid p_1,..., p_{t-1}\right) = E\left(\beta_t^2 s_{it-1}^2 \mid p_1,..., p_{t-1}\right) = \beta_t^2 \Lambda_{t-1}.$$

Substituting (A.2) and (A.4) into (A.1) yields (1).

As to the expected trading volume in (2), we first start by defining the trading volume as

(A.5) $$\begin{aligned} E(TV_t \mid p_1,..., p_{t-1}) &\equiv \tfrac{1}{2} E\left(\sum_{i=1}^{M} |\Delta x_{it}| + |u_t| + \left| \sum_{i=1}^{M} \Delta x_{it} + u_t \right| \;\middle|\; p_1,..., p_{t-1} \right) \\ &= \tfrac{1}{2} E\left(\sum_{i=1}^{M} |\beta_t s_{it-1}| + |u_t| + \left| \sum_{i=1}^{M} \beta_t s_{it-1} + u_t \right| \;\middle|\; p_1,..., p_{t-1} \right), \end{aligned}$$

where the first term measures the trading volume contributed by the informed traders, the second term, by the liquidity traders, and the last term, by the market maker. Notice that conditional on the past prices, all the random variables inside the absolute value operator are normally distributed with zero mean. Therefore, by the property of normal random variables,

(A.6) $$\begin{aligned} E(TV_t \mid p_1,..., p_{t-1}) &\equiv \tfrac{1}{2} E\left(\sum_{i=1}^{M} |\Delta x_{it}| + |u_t| + \left| \sum_{i=1}^{M} \Delta x_{it} + u_t \right| \;\middle|\; p_1,..., p_{t-1} \right) \\ &= \tfrac{1}{2} E\left(\sum_{i=1}^{M} |\beta_t s_{it-1}| + |u_t| + \left| \sum_{i=1}^{M} \beta_t s_{it-1} + u_t \right| \;\middle|\; p_1,..., p_{t-1} \right), \end{aligned}$$

Note that

(A.6)

Then, a substitution of (A.4) and (A.6) into (A.5) proves (2).

Table 1: Summary Statistics

This table provides the summary statistics of the normalized price, price change and volume series. For the sake of simplicity, let *-t* day *variable* denote the value of the *variable* as of *t* days prior to the earnings announcement. Then, the normalized price is obtained by first setting the -10 day stock price to be 100. We then take the return series from -9 days, and generate the index stock prices. Once all the normalized prices are calculated, for each announcement, we calculate the price volatilities by taking the square of the difference between adjacent normalized prices. With respect the normalized trading volume, we first calculate -10 day 'unit trading volume'. The unit trading volume measures the hypothetical trading volume if the -10 day stock price and the trading volume were 100 and 1, respectively. This can be done by dividing the -10 day stock price by 100. Once the unit trading volume is calculated, we then obtain the normalized trading volume by multiplying the actual trading volume by the unit trading. The numbers in the bracket, [], are the numbers of observations in the corresponding sample. Each number shows cross-sectional averages across the announcements. The daily volume is in 1000 normalized shares.

days to earnings anncemnt.	Whole Sample [824]			Large Cap. [274]			Medium Cap. [275]			Small Cap. [275]		
	Price	P^2	Volume	Price	P^2	Volume	Price	P^2	Volume	Price	P^2	Volume
-9	99.79	7.13	53.72	99.77	5.71	143.56	100.04	3.93	15.80	99.55	11.75	2.14
-8	99.59	7.77	50.41	99.40	2.86	132.16	100.03	5.12	17.04	99.36	15.31	2.35
-7	99.36	7.89	51.88	99.07	3.26	135.63	99.89	4.60	17.75	99.13	15.79	2.56
-6	99.11	6.48	51.03	98.80	3.04	134.43	99.55	3.74	16.30	98.98	12.65	2.70
-5	98.97	9.39	53.41	98.60	2.76	141.84	99.15	3.96	16.16	99.17	21.44	2.56
-4	98.78	6.09	56.45	98.44	2.71	148.29	99.10	5.12	18.81	98.80	10.41	2.60
-3	98.67	7.39	51.36	98.22	3.18	136.69	98.96	3.67	15.64	98.81	15.30	2.07
-2	98.57	5.36	56.55	97.93	2.90	152.76	98.90	4.02	14.70	98.89	9.14	2.53
-1	98.31	10.30	56.69	97.77	3.23	152.40	98.62	3.98	15.40	98.56	23.67	2.61
0	98.28	20.66	77.68	97.82	5.06	200.90	98.33	16.00	27.89	98.71	40.86	4.71

Table 2: Parameter Estimates of the General Model

This table provides the GMM estimates of the general model based on Foster and Viswanathan (1996). The model is estimated using the normalized price volatility and normalized trading volume series. Prices are normalized so that the price of 10 days prior to the earnings announcement is $100. The trading volumes are in 1000 shares. For the specifics on normalization, refer to Section II. There are 4 parameters to estimate in the model: the number of informed traders, *M*, the covariance between any two signals, $_0$, the difference between initial variance and covariance of the signals, , the amount of liquidity trading, $_u$. This table provides the estimates of the variance of private signals, $_0$, and the correlation between any two private signals, $_0$. The former is calculated by adding $_0$ and , and the latter, by dividing $_0$ by $_0$. The numbers in [] show the number of observations in the corresponding sample. The GMM estimators are asymptotically normally distributed. The numbers in () are the standard errors of the estimates. The asterisk, *, indicates that the null hypothesis that the true value is zero is rejected at 5% significance level. For the number of informed traders, we provide z-statistics in <> for testing a null hypothesis that the number of informed traders is larger than 1. Here also, * indicates that the null hypothesis is rejected at 5% significance level. For the variance of private signals, 0, we provide in {}, the square root of the estimate, i.e., the standard deviation.

	no. of informed traders, *M*	Var. of private signals, $_0$	Cov. of private signals, $_0$	$_0$ - $_0$,	Corr. of private signals, $_0$	liquidity trading, $_u$
	Panel A: 10-day trading Horizon					
whole sample [824]	1.64 <1.54>	41.74 {6.46}	1.96 (0.06)*	39.78 (0.95)*	0.05	46.42 (4.05)*
large firms [274]	1.18 <1.45>	28.49 {5.34}	1.32 (0.07)*	27.17 (0.76)*	0.05	123.86 (9.75)*
medium firms [275]	1.35 <0.57>	44.43 {6.67}	-16.64 (1.81)*	61.07 (2.51)*	-0.37	12.49 (0.94)*
small firms [275]	1.88 <0.92>	63.69 {7.98}	0.94 (0.32)*	62.74 (1.85)*	0.01	1.79 (0.26)*
	Panel B: 5-day trading Horizon					
whole sample [824]	1.06 <0.02>	36.85 {6.07}	24.99 (2.00)*	11.86 (3.01)*	0.68	49.26 (4.44)*
large firms [274]	1.01 <0.01>	20.30 {4.51}	20.26 (14.12)	0.04 (14.11)	1.00	132.86 (11.00)*
medium firms [275]	1.04 <0.10>	25.74 {5.07}	22.94 (3.19)*	2.80 (11.00)	0.89	12.30 (1.08)*
small firms [275]	1.09 <0.02>	60.69 {7.79}	42.07 (9.52)*	18.62 (11.88)	0.69	1.89 (0.21)*

Table 3: Test of Models: Heterogeneous *vs.* Homogeneous Information

This table provides the *DM* (Distance Metric) statistics for testing the models of homogeneous information against the general model of heterogeneous information. There are two models of homogeneous information: HS and Kyle. In HS, informed traders receive an identical signal. Moreover, in Kyle there is a monopolistic informed trader. We first estimate FV, HS and Kyle, and obtain , where n is the number of observations, $Q_i()$, the minimized value of the criterion function evaluated at the GMM estimates for HS or Kyle, and $Q()$,the minimized value of the criterion function evaluated at the GMM estimates for FV. The *DM* statistic converges to a chi-square distribution with 1 degree of freedom under HS, and 2 degrees of freedom under Kyle. Panel A shows the results for 10-day trading horizon, and Panel B, for 5-day horizon. The numbers in [] are the number of observations in the sample. The * indicates that the null hypothesis is rejected at 5% significance level.

	Panel A: 10-trading horizon		Panel B: 5-day trading horizon	
	HS *DM*	Kyle *DM*	HS *DM*	Kyle *DM*
whole sample [824]	15.00*	15.00*	1.15	1.15
large firms [274]	3.12	3.12	0.71	0.71
medium firms [275]	2.09	2.09	0.33	0.33
small firms [275]	6.49*	6.49*	0.17	0.17

Table 4: Strategic Trading and the Timing of Information Resolution

This table provides the *pseudo-DM* (Distance Metric) statistics for two separate scenarios of 5-day trading horizon. The first scenario assumes that the announcement was actually made on the announcement date, while the second scenario assumes that the announcement was made a week prior to the actual announcement. For each scenario, the *pseudo-DM* statistic is evaluated by the following way. First, we estimate both the general model, FV, and the model of strong-form efficient market, EFF, Then, we obtain

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where n is the number of observations, $Q()$, the minimized value of the criterion function evaluated at the GMM estimates for EFF, and $Q()$, the minimized value of the criterion function evaluated at the GMM estimates for FV. These two models are not nested in each other. Therefore, the limiting distribution of the *pseudo-DM* statistics is not known. The numbers in the bracket, [], show the number of observations in the corresponding sample.

	pseudo-DM statistics for 5-day trading horizon	
	true announcement date	false announcement date
whole sample [824]	23.10	-35.27
large cap. firms [274]	17.85	-27.98
medium cap. firms [275]	3.64	-9.27
small cap. firms [275]	7.92	-2.15