The Probability of Informed Trading and the Performance of Stock in an Order-Driven Market

Tai Ma
National Sun Yat-Sen University
Ming-hua Hsieh
National Chengchi University
Jang-hung Chen
National Sun Yat-Sen University

Abstract

In this paper we estimate the probability of informed trading (P_i) in an order-driven stock market as well as perform a comprehensive analysis on the interrelations among probability of informed trading and three common performance indicators, i.e., liquidity, volatility and efficiency. We find that uninformed traders exhibit price chasing behavior even over very short time interval and that volatility in stock price attracts uninformed traders. Using 3SLS which takes into consideration the endogeneity of the probability of informed trading and the liquidity, volatility and efficiency measures, our empirical results provide new evidence on market microstructure literature. We find that P_i and the volatility and liquidity of stocks are simultaneously determined. Higher P_i leads to lower liquidity and higher volatility, and vice versa. Firms with larger size, higher ownership concentration and lower turnover have higher probability of informed trading.

Introduction

The existence of information asymmetry among market participants makes informed trading a very important issue from many respects. Uninformed traders would want to learn from the informed about the true value of the asset, regulators are interested in the evidence of insider trading, and the academics are interested in the behavior of the market participants and the process by which private information is incorporated into prices. A most challenging question is how can we tell the probability of informed trading for each stock from publicly available data? Hasbrouck (1991a) points out that the magnitude of the price effect of information is a positive function of the proportion of potentially informed traders, the probability of a private information signal, and the precision of the private information. However, the probability of informed trading is not directly observable and must be estimated from observable trade data such as quotes, transaction prices and volumes.

Past researches in this area may be roughly categorized into three groups: (1) Works that are related to the estimation of the magnitude of the price impact of information or trade informativenss, such as Hasbrouck (1991a,1991b), and Madhavan and Smidt (1991); (2) Studies that use some proxy variables to measure information asymmetry, most notably is the bid ask spread. Bagehot (1971) is the first to suggest that bid ask spread can reflect the adverse selection problem facing the market maker. Numerous studies later use bid ask spread as a measure for information asymmetry (see, for example, Jaffe and Winkler, 1976; McInish and Wood, 1992; Foster and Viswanathan, 1990, 1993a, 1993b; and Chiang and Venkatesh, 1988, among others) [Note 1]. Other measures of informed trading include the proportion of insiders ownership (e.g., Chiang and Venkatesh, 1988), firm size (e.g., Hasbrouck, 1991b), the number of trades (Jones et al, 1994), trade volume and trade size (e.g., Keim and Madhavan, 1996; Easley, Kiefer and O'Hara, 1997b) [Note 2]; and (3)Sequential trade models that describe the trading process and decode the probability of informed trading by econometrically examining its manifestation on observable trade data using specific statistical technique such as maximum likelihood estimation (e.g., Easley et al, 1996) or GMM (Handa, Schwartz and Tiwari, 2003).

These studies, among others, all analyze the issue of information content from one point or another, but only a few of them deal with the direct estimation of the probability of informed trading. Easley, Kiefer, O'Hara and Paperman (1996) (EKOP hereafter) and Easley, Kiefer and O'Hara (1997a, 1997b) pioneer a series of studies on estimating the probability of informed trading. In their models, information event is assumed to occur once per day, and maximum likelihood estimation technique is used to estimate the relevant parameters, including the probability of informed trading, given actual numbers of buys and sells. One major difference in Easley, Kiefer and O'Hara (1997b) from their previous papers is that they incorporate trade size into the trade process and allow for history dependence in noise trader's decision, and they assume noise trader's decision at time t depends on the buy and sell decision at time t-1. They find that the probability of information-based trading is lower for high volume stocks, and large trade tends to have higher information content. However, the conclusion is obtained by a simple comparison between subsamples without controlling for other factors. Although the EKOP model has some limitations, numerous papers have applied EKOP model to estimate information-based trading (e.g., Brockman and Chung, 2000, Chung, Li and McInish, 2005).

In this paper, we are interested in measuring the probability of informed trading. While almost all studies in information trading concentrate on quote-driven markets [Note 3], we modify Easley et al.'s (1997b) trade model and estimate the probability of informed trading in an order-driven market. As more and more major markets have adopted the order-driven trading mechanism, it would be interesting to see whether the same result applies in such market where individual investors submit competing bid and ask orders on the automatic limit order book. Our study is different from previous in three aspects, first of all, unlike EKOP model which assumes one event per day, we allow for intra day event. Secondly, we use option pricing model and other simpler technique to estimate the probability of informed trading, rather than more complicated MLE or GMM techniques. Hence our model does not need the independence assumption across days as in EKOP-type model [Note 4]. Finally, we assume noise trader's decision at time t depends on the price movement in period t-1, rather than the buy and sell decision at t-1 as assumed in Easley et al. Our assumption is consistent with the trend chasing behavior of noise traders observed in many studies, e.g., Andreassen and Kraus (1988), Frankel and Froot (1989) and DeLong et al. (1990), among others, and the empirical result also confirms our assumption on noise trader's price chasing behavior.

In addition to estimate the probability of informed trading, we are also interested in exploring the relationships between informed trading and market performance. The significance of the probability of informed trading can be best manifested through its interaction with the efficiency, liquidity and volatility of the market. Although a plethora of researches has explored the theoretical implication between informed trading and liquidity or efficiency [Note 5], surprisingly little empirical work can be found for a comprehensive analysis on the interrelations between the probability of informed trading and various stock performance measures. For example, there is little empirical study thus far on the relation between efficiency (or volatility) and the estimated probability of informed trading, although it is one of the key propositions in market microstructure theories that informed trading enhances efficiency. Easley et al. (1996) first explore the relation between liquidity and the probability of informed trading; however, only simple comparison of means was presented in their study. Brockman and Chung (2000) and Chung and Li (2003) adopt EKOP model and examine the relationship between the probability of informed trading and liquidity in Hong Kong and other markets. Cross-sectional OLS regression is applied in their study where liquidity is treated as the dependent variable. However, OLS is not an appropriate estimation method when liquidity and the probability of informed trading are endogenously determined. In fact, theories on informed trading suggest that the order strategy of informed traders depends on the liquidity, volatility as well as efficiency of the stock, and these performance measures in turn are a result of the endogenously determined trading of the informed and uninformed [Note 6]. The second purpose of this study is to do a comprehensive investigation on the interaction between the probability of informed trading and the liquidity, efficiency as well as volatility of stocks. Unlike previous studies, structural models of the above variables are built and estimated using three stage least squares. To the best of our knowledge, this is the first study that empirically explores the interactions among the probability of informed trading and all of the key performance measures (i.e., liquidity, volatility and efficiency), while adopting a system of equations approach which takes into consideration the endogeneity of the variables.

Our empirical estimation of the probability structure reveals two interesting findings about the behavior of the uninformed traders. Uninformed traders exhibit price chasing behavior even over very short interval, they tend to buy when the price in the previous trading period goes up and sell when the price in the previous trading period declines. We also find that volatility in prices attracts noise traders to trade. Uninformed traders are more likely to trade when price moves in the previous trading interval. The results of the three-stages least squares (3SLS) regressions indicate that the probability of informed trading and two popular performance measures, i.e., liquidity and volatility, are simultaneously determined. Higher probability of informed trading leads to lower liquidity and higher volatility, and vice versa. This finding does not support Admati and Pfleiderer (1988)'s proposition that informed traders will follow the trading pattern of the uninformed whose trades tend to cluster together (i.e., liquidity attracts informed trading), since we do not find that liquidity induces informed trading. Rather, our finding is consistent with Foster and Viswanathan (1990) argument that liquidity is lower when the probability of informed trading is high.

On the other hand, the probability of informed trading and the efficiency measure do not appear to be simultaneously determined. Specifically, higher efficiency leads to higher probability of informed trading, while there is no evidence that higher probability of informed trading leads to higher efficiency. One possible explanation of the somewhat surprising finding that informed trading does not enhance efficiency is that the samples in this study are firms listed in the Taiwan Gre Tai Exchange, where the firm's sizes are smaller and the trading volumes are also lower than those listed in the Taiwan Stock Exchange. Therefore, informed traders in these stocks are much less competitive. As suggested by Kyle (1985), when there is monopolistic informed trader, the price discovery process will be slower given the profit maximizing behavior of the monopolistic informed trader [Note 7]. Our finding that high probability of informed trading does not lead to more efficient pricing for stocks listed in Taiwan Gre Tai Exchange illustrates the importance of competition to market efficiency, that is, informed trading alone does not lead to efficiency.

Finally, we find that firms with larger size, higher ownership concentration and lower turnover have higher probability of informed trading. It is interesting to compare our result with Hasbrouck (1991b) or Easley et al. (1996) who find that firms with larger size have lower probability of informed trading. We find that, after controlling for other factors, firms with larger size have higher probability of informed trading. It is also interesting to see that turnover is negatively related with informed trading in our study. Turnover ratios in Taiwan stock market are commonly regarded as an index for noise traders, high turnover is associated with more noise trading. The negative relation between turnover and the probability of informed trading supports the viewpoint that turnover ratio is a noise trading signal in Taiwan, rather than a proxy for informed trading as suggested by some of the studies in the U.S.

The Trade Model of Order-Driven Market

The stock exchange in Taiwan is a pure order-driven market where orders are accumulated and matched against each other via the automated central limit order book at frequent call intervals (less than one minute between calls), there is no official market maker providing bid and ask quotations. On-line market report on the latest transaction prices, market bid and ask quotes and volumes for each stock is available to all investors. The bid and ask quotations of the market are the best prices in the limit order book provided by various traders. From this respect, we may think that there are numerous competitive market makers and the expected profit is zero [Note 8].

We assume two types of traders in our trade model: informed traders and noise (uninformed) traders. Both types of traders trade in the market over $t = 1, \ldots, T$ intraday trading periods. The percentage of each type of traders is fixed. We denote P_i the percentage of informed traders, and $P_u = 1 - P_i$ the percentage of uninformed traders in the market. For each trading period, an information event occurs independently with probability α. These events are good news with probability , or bad news with probability $1-\delta$. The value of information events is fully realized at the end of the trading period.

Informed traders trade stocks at each trading period *t* according to the information event occurring at that period, and the corresponding action is simply to buy (B) if the event is good news, to sell (S) if the event is bad news, and no action is taken (N) if there is no event. In other words, in non-event periods all transactions come from the uninformed. Therefore, P_i can be regarded as a measure for the probability of information trading. Since we assume the information arrives over time independently, the decisions of the informed traders are independent over time. Unlike informed traders whose decisions are independent across time, we assume the behavior of the noise traders often exhibits positive feedback pattern [Note 9]. In order to reflect this evidence of dependency in trading behavior over time, we allow for history dependence in the decisions of the uninformed traders. However, unlike Easley et al. (1997b) who assume that the uninformed trader chooses a specific trade decision at time *t* given the buy or sell trade type at time *t-1*, we believe the uninformed trader is more influenced by the direction of the price movement in the previous period rather than by trade types. Uninformed traders are more likely to buy when the price rises in the previous trading interval, but they do not necessarily follow the previous buy action if the price goes down in the previous period, i.e., the uninformed tend to buy on uptrend and sell on downtrend in our model. These behaviors of the uninformed can be captured by assigning appropriate probabilities of trading and buying decisions for the uninformed. If the price change in the previous trading period is an up movement (*U*), a noise trader chooses to trade with probability $\beta(U)$ and not to trade with probability 1-$\beta(U)$; and if he decides to trade in this case, he will choose to buy with probability $\gamma(U)$ and to sell with probability 1 -$\gamma(U)$. Similarly, if no price change (M) is realized in the previous trading period, the probability that a noise trader will trade is and 1- $\beta(M)$ if not; and if he does trade he will choose to buy with probability $\gamma(M)$ and to sell with probability 1-$\gamma(M)$. Finally, if the stock price in the previous trading period goes down (*D*), a noise trader chooses to trade with probability $\beta(D)$ and not to trade with probability 1 -$\beta(D)$, and given the decision to trade, he will choose to buy with probability $\gamma(D)$ and to sell with probability 1 -$\gamma(D)$. In addition, the decisions only depend on the price movement of previous trading period. That is, noise traders trade stocks according to a stationary policy (to be shown below) associated with an Markov decision process, e.g. see Hiller and Lieberman (2005), that are parameterized by the price movement of the stock in the previous trading period. Although these are simplified assumptions, it does capture the spirit of the buy-high, sell-low behavior of a typical individual investor in the Taiwanese stock market. Our empirical results also indicate that these assumptions are a reasonable simplification of the market structure. In sum, the noise traders' behavior can be modeled by a Markov decision process having state space {U, M, D}, decision space {B, N, S}, and following the stationary policy:

And the informed traders' behaviors can be modeled by a Markov decision process having state space {*g, n, b*}, decision space {B, N, S}, and following the stationary policy:

	B	N	S
g	*1*	*0*	*0*
n	*0*	*1*	*0*
b	*0*	*0*	*1*

Estimation of the Model Parameters

The model parameters to be estimated are P_i, α, β, $\beta(i)$, and $\gamma(i)$, $i \in \{U, M, D\}$ which will be estimated from the actual transactional data. The data set for the empirical estimation contains the 5-minute transactional data of the bid, the ask and the transaction prices as well as the corresponding volumes for stocks traded in the Taiwan OTC Stock Exchange from the beginning of January to the end of December in 1999. We deleted those firms that had been listed for less than a year in the study period, a total of 107 stocks and over 960,000 observations are included. We estimate these model parameters in steps. First, we estimate the probabilities of information events (α and δ). To achieve this goal, we assume that the price process follows a geometric Brownian motion. Thus we can approximate the geometric Brownian motion by a trinomial tree. Actually, trinomial trees are very accurate approximations in this case, because the trading interval is very short (i.e., 5-minute). Given the history of past prices of a stock, it is straightforward to estimate the up factor (*u*), down factor (*d*), and associating branching probabilities (*p, q)* for a trinomial tree; see Hull (2006), for example. On the average, we can assume an up-movement in price is due to good news, and a down-movement in price is by bad news. Thus, we can equate the following two equations by matching the probability of up (down) movement with the probability of good news (bad news).

$$\alpha\,\delta = p$$
$$\alpha(1-\delta) = q \qquad (1)$$

Solving α ,δ in terms of *p* and *q*, we can obtain estimates for the probability of an information event (α), and the probability that the event is good news (δ).

Second, we will estimate $\gamma(i), i \in \{U, M, D\}$. To do so, we need to assign the type of the events (i.e., *g*, *b*, or *n*) for each trading period of the data. To determine the event type for each trading period, a logit-like model is adopted. The ratio of the volume of buy orders to the sum of the volumes of buy and sell orders at each trading period is used as a decision variable. If this variable is greater than an upper threshold (λ_g), we assign good news as the event type. If this variable is less than a lower threshold (λ_b), we assign bad news as the event type. Otherwise we assign no event as the event type. The two thresholds are determined numerically for each stock by maximizing the likelihood function of the logit-like model. Recall that informed traders buy (sell) only when there is good (bad) news, and on non-event periods all trades come from noise traders. Therefore, if the event type is judged correctly, the sell (buy) orders in good (bad) event periods should come from the same uninformed population as the sell (buy) orders in nonevent periods. Similarly, the total trading volume in bad event periods should come from the same population as the total trading volume in good event periods. We can find the upper and lower thresholds by minimizing the sum of variances of (Bb-Bn), (Sg-Sn), and [(Bg+Sg)-(Bb+Sb)]. Table 1 shows the thresholds estimated for each stock. The ranges of λ_g and λ_b are computed to be between 0.55 to 0.85, and 0.15 to 0.45, respectively. After the event type for each trading period is identified, the data set is partitioned into 9 parts. Each part has a different combination of event type (*n, g, b*) and price movements (*U, M, D*). For example, the three parts corresponding to non-event periods are (*n, U*), (*n, M*), and (*n, D*). Since in non-event periods all trades come from uninformed traders, transactions in the non-event data set provide direct estimates for $\gamma(i), i \in \{U, M, D\}$. For example, let *k* be the number of elements in the set (*n, U*), Bt be the volume of buy orders and St be the volume of sell orders in a non-event period t, then

$$\frac{1}{k}\sum_{t=0}^{k}\frac{B_t}{B_t+S_t}$$

is a direct estimate of $\gamma(U)$, the probability of a decision to buy for an uninformed trader when price moves up in the previous trading interval. Similarly, we can estimate $\gamma(M)$ and $\gamma(M)$.

Table 1:
The Event Type Thresholds Estimates

λ_g (λ_b) is the upper(lower) threshold for event type.
where λ_g is the thresholds for good news, and λ_b is the thresholds for bad news

Company ID	4204	4301	4302	4401	4403	4404	4502	4503	4504	4506	4508	4511	4512	4513	4514	4515	46101	4603	4604	4605	4607
λ_g	0.75	0.67	0.61	0.61	0.61	0.72	0.85	0.83	0.7	0.74	0.81	0.72	0.67	0.79	0.75	0.82	0.77	0.8	0.76	0.77	0.83
λ_b	0.3	0.27	0.36	0.36	0.27	0.28	0.28	0.34	0.2	0.26	0.3	0.23	0.25	0.26	0.2	0.27	0.29	0.17	0.21	0.29	0.28
Company ID	4608	4701	4702	4703	4705	4706	4707	4801	5001	5004	5005	5006	5007	5008	5009	5302	5305	5306	5309	5310	5311
λ_g	0.78	0.83	0.83	0.74	0.7	0.74	0.63	0.82	0.63	0.83	0.84	0.74	0.68	0.81	0.81	0.69	0.72	0.79	0.84	0.66	0.79
λ_b	0.22	0.22	0.22	0.25	0.28	0.27	0.26	0.27	0.3	0.28	0.3	0.19	0.17	0.15	0.25	0.16	0.16	0.17	0.34	0.16	0.21
Company ID	5312	5313	5314	5315	5317	5318	5319	5322	5323	5324	5325	5327	5328	5332	5333	5335	5336	5337	5342	5344	5345
λ_g	0.78	0.79	0.83	0.82	0.82	0.84	0.83	0.82	0.8	0.67	0.73	0.67	0.82	0.82	0.84	0.83	0.72	0.71	0.83	0.81	0.82
λ_b	0.18	0.15	0.15	0.15	0.17	0.22	0.16	0.21	0.18	0.15	0.16	0.22	0.24	0.16	0.2	0.2	0.18	0.16	0.16	0.17	0.15
Company ID	5347	5351	5352	5353	5354	5355	5356	5357	5358	5359	5360	5361	5362	5363	5364	5365	5502	5503	5504	5505	5506
λ_g	0.75	0.83	0.79	0.82	0.78	0.79	0.74	0.84	0.84	0.69	0.83	0.85	0.81	0.82	0.7	0.78	0.85	0.81	0.76	0.7	0.82
λ_b	0.18	0.17	0.17	0.18	0.15	0.22	0.18	0.24	0.21	0.2	0.2	0.16	0.16	0.15	0.19	0.16	0.15	0.18	0.2	0.17	0.2
Company ID	5509	5511	5513	5514		5604	5605	5701	5702	5810	5817	5818	6001	6003	6015	6016	8902	8903	8905	89069	8908
λ_g	0.85	0.7	0.7	0.75	0.78	0.85	0.84	0.77	0.83	0.66	0.85	0.84	0.67	0.81	0.83	0.66	0.76	0.84	0.7	0.84	0.85
λ_b	0.25	0.21	0.2	0.17	0.22	0.15	0.17	0.16	0.21	0.35	0.15	0.29	0.22	0.19	0.16	0.16	0.17	0.15	0.17	0.17	0.21
Company ID	8910	8913																			
λ_g	0.84	0.79																			
λ_b	0.24	0.17																			

Third, we will estimate P and $\beta(i), i \in \{U, M, D\}$. The probability to trade for an uninformed trader at t, given the price movement in t-1, is as

$$\beta(o_{t-1}) = (S_t + B_t) / (P_u \hat{T}) \tag{2}$$

where o represents the event type in the previous interval, $\hat{T}$ denotes the average trading volume of the trading interval t, so $\beta(o_{t-1})$ is the ratio of the actual volume for trade to the expected trading volume of the uninformed trader at time t. Since P_u is unknown, we cannot solve $\beta(o \quad)$ by equation (2) alone. However, we will be able to solve $\beta(o \quad _1)$ as well as the probability of informed trading, P_i, numerically by equations (2), (7) and (8).

Let V be the true stock price, $\underline{V}$, $\bar{V}$, and V^* be the value of the stock conditioned on bad news, good news, and no event, respectively. We can regard the ask price as the expectation of V conditioned on a "buy" decision. That is,

$$A \;=\; E[V \quad | B] = V \quad + V\, P(V \mid B) + V \quad P(V \quad \mid B) \tag{3}$$

By Bayes' formula, we have

$$P(V \mid B) = \frac{P(V = V)\cdot P \quad B \mid V = V}{(B \mid V = V) + P(V = \bar{V})\cdot P(B \mid V = \bar{V}) + P(V = V^*)\cdot P(B \mid V = V^*)} \tag{4}$$

where , $P(B \mid V = V)$, $P(B \mid V = V^*)$ denote the conditional probabilities of a buy decision given the corresponding event type. According to the trade model, it is easy to be shown

$$P(B \mid V = V) = \alpha(1-\delta),\ P(V = V) = \alpha\delta, \qquad = 1-\alpha$$
$$P(B \mid V = V) = b,\ P(B \mid V = V^*) = b,\ P(B \mid V = V) = b + P_i \tag{5}$$

he $b = P_u\, \beta(o \quad)$

Substituting (5) into (4), we have

$$= \frac{\alpha(1-\delta)\cdot \underline{b}}{\alpha(1-\delta)\cdot \underline{b} + \alpha\delta \cdot \underline{(b+P_i)} + (1-\alpha)\cdot \underline{b}} = \frac{\alpha(1-\delta)\cdot \underline{b}}{\underline{b+\alpha \cdot P_i}} \tag{6}$$

Similarly, we can compute $P(\underline{V} \mid B)$ and $P(V^* \mid B)$. Substituting these terms into equation (3), we finally have

$$\text{Ask} = \frac{V \cdot \alpha(1-\delta)\cdot \underline{b} + \overline{V}\cdot \alpha\delta \cdot (\underline{b}+P_i) + V^* \cdot (1-\alpha)\cdot \underline{b}}{\bar{s} + \alpha(1-\delta)\cdot P_i} \tag{7}$$

With the same argument, it can be shown that

$$\text{Bid} = \frac{\underline{V}\cdot \alpha(1-\delta)\cdot (P_i + \bar{s}) + \overline{V}\cdot \alpha\delta \cdot \bar{s} + V^* \cdot (1-\alpha)\cdot \underline{\bar{s}}}{\bar{s} + \alpha(1-\delta)\cdot P_i} \tag{8}$$

where $\bar{s} = P_u \cdot \beta(o_{t-1})\cdot(1-\gamma(o_{t-1}))$

Since , , , , and are known, $\overline{V} = S(1+\mu)$, $= S(1-d)$, S is the transaction price, and $\beta(o_{t-1})$ can be substituted by equation (2), it is then straightforward to solve P_i, the probability of informed trading, by equations(7) and (8).

Table 2:
Estimates of the Probabilities to Trade for Uninformed Traders under Different Previous Price Movements

, $\beta(M)$, and $\beta(D)$ denote the probabilities to trade for an uninformed trader when the price moments in the previous trading period are up, no change, and down, respectively

Company ID	4204	4301	4302	4401	4403	4404	4502	4503	4504	4506	4508
$\beta(U)$	0.57982	0.65148	0.72334	0.54183	0.65618	0.64526	0.63715	0.60152	0.58216	0.63802	0.66346
$\beta(M)$	0.4316	0.50006	0.41006	0.48673	0.51113	0.4607	0.50154	0.45237	0.49581	0.50334	0.48202
$\beta(D)$	0.45606	0.51163	0.69963	0.50108	0.50937	0.5495	0.56912	0.5072	0.53044	0.60399	0.59066
Company ID	4511	4512	4513	4514	4515	46101	4603	4604	4605	4607	4608
$\beta(U)$	0.56792	0.58128	0.67858	0.60989	0.58301	0.61388	0.60762	0.66127	0.34271	0.66877	0.61622
$\beta(M)$	0.58116	0.42843	0.4433	0.48461	0.44674	0.47592	0.62972	0.51599	0.51752	0.46393	0.52033
$\beta(D)$	0.56028	0.53654	0.56382	0.60151	0.51016	0.59231	0.61204	0.56564	0.23235	0.533889	0.57727
Company ID	4701	4702	4703	4705	4706	4707	4801	5001	5004	5005	5006
$\beta(U)$	0.65872	0.62388	0.63922	0.85171	0.64194	0.66791	0.68179	0.62032	0.65303	0.67845	0.68099
$\beta(M)$	0.47715	0.50923	0.44326	0.47363	0.40017	0.46344	0.49879	0.52548	0.48278	0.46887	0.46805
$\beta(D)$	0.61352	0.55869	0.62065	0.59627	0.51731	0.53626	0.58511	0.55886	0.6012	0.55758	0.58941
Company ID	5007	5008	5009	5302	5305	5306	5309	5310	5311	5312	5313
$\beta(U)$	0.57642	0.7317	0.65299	0.69941	0.61496	0.64257	0.63858	0.77753	0.64582	0.62415	0.6449
$\beta(M)$	0.57623	0.57571	0.53104	0.50743	0.52194	0.58065	0.51769	0.53411	0.4837	0.52649	0.58746
$\beta(D)$	0.56026	0.63163	0.57741	0.64295	0.59885	0.62313	0.59699	0.64198	0.63979	0.56475	0.62593
Company ID	5314	5315	5317	5318	5319	5322	5323	5324	5325	5327	5328
$\beta(U)$	0.63671	0.61901	0.59239	0.59912	0.64071	0.56809	0.59779	0.6291	0.564	0.59251	0.59257
$\beta(M)$	0.62174	0.58234	0.55385	0.60095	0.61388	0.61406	0.52493	0.53303	0.5508	0.49871	0.53525
$\beta(D)$	0.62991	0.6025	0.5853	0.60332	0.63316	0.56153	0.61179	0.58896	0.52906	0.61145	0.57344
Company ID	5332	5333	5335	5336	5337	5342	5344	5345	5347	5351	5352
$\beta(U)$	0.60641	0.6541	0.60947	0.66155	0.64587	0.70976	0.59895	0.60202	0.62942	0.60891	0.62811
$\beta(M)$	0.52997	0.51238	0.55868	0.50034	0.46209	0.52464	0.57876	0.54175	0.64983	0.602	0.58199
$\beta(D)$	0.60771	0.62041	0.5885	0.60808	0.56649	0.62601	0.61509	0.61133	0.64755	0.60727	0.59001
Company ID	5353	5354	5355	5356	5357	5358	5359	5360	5361	5362	5363
$\beta(U)$	0.69905	0.63675	0.61412	0.6883	0.44363	0.65861	0.65734	0.53481	0.64395	0.63078	0.65222
$\beta(M)$	0.54168	0.56072	0.44427	0.48448	0.52682	0.59266	0.54591	0.48568	0.59255	0.49791	0.5019
$\beta(D)$	0.68711	0.6206	0.50872	0.5543	0.40435	0.65328	0.67428	0.53014	0.61286	0.61697	0.65444
Company ID	5364	5365	5502	5503	5504	5505	5506	5509	5511	5513	5514
$\beta(U)$	0.6031	0.69084	0.61676	0.63484	0.72353	0.67884	0.69199	0.54085	0.84588	0.63991	0.67678
$\beta(M)$	0.57858	0.53659	0.51774	0.52946	0.51339	0.58994	0.48888	0.45851	0.42644	0.50795	0.49979
$\beta(D)$	0.59817	0.67608	0.61047	0.57621	0.51712	0.55221	0.51485	0.54964	0.41567	0.58286	0.58558
Company ID	5603	5604	5605	5701	5702	5810	5817	5818	6001	6003	6015
$\beta(U)$	0.53334	0.55744	0.69535	0.74442	0.7284	0.67982	0.72597	0.70145	0.63793	0.68602	0.62686
$\beta(M)$	0.40717	0.4867	0.49711	0.53436	0.50228	0.60957	0.5709	0.60591	0.63761	0.62191	0.64932
$\beta(D)$	0.32691	0.51501	0.63115	0.60651	0.59172	0.64643	0.68322	0.63995	0.63552	0.64487	0.60252
Company ID	6016	8902	8903	8905	89069	8908	8910	8913			
$\beta(U)$	0.61466	0.66564	0.74978	0.74664	0.63783	0.54291	0.61303	0.58597			
$\beta(M)$	0.57728	0.46819	0.5	0.38531	0.4549	0.48805	0.47596	0.49958			
$\beta(D)$	0.60937	0.57048	0.6197	0.64366	0.51858	0.53232	0.45019	0.55082			

Using the method described above, we estimate P_i (the percentage of informed traders), $\beta(i)$ (the probabilities of trading of a noise trader), and (the probabilities of buy when a noise trader decides to trade) for the transactional data. The results are listed in Tables 2, 3 and 4.

It is interesting to see from Table 2 that for most stocks in the sample, > > . This result indicates that price volatility attracts noise traders to trade. In addition, > for all firms, indicating noise traders' stronger willingness to trade on up trend than on down trend. One possible explanation for this asymmetry in trading behavior is the restriction to short selling at down tick.

Table 3 shows the estimates of . We can see that $> \gamma(2) >$ for most stocks. In other words, uninformed traders are more willing to buy (sell) when prices rise (fall) in the previous trading period, which is consistent with the positive feedback behavior assumption for noise traders in the model.

Table 3:
Estimates of the Probabilities to buy by Uninformed Traders under Different Previous Price Movements

, $\gamma(M)$, and $\gamma(D)$ denote the probabilities to buy when a noise trader decides to trade, given that price moments in the previous trading period are up, no change, and down, respectively

Company ID	4204	4301	4302	4401	4403	4404	4502	4503	4504	4506	4508
	0.53734	0.52462	0.52458	0.53661	0.5009	0.51773	0.51046	0.52681	0.54018	0.51995	0.52099
	0.52988	0.7	0.49837	0.49575	0.48229	0.49158	0.49378	0.50913	0.48815	0.49847	0.50177
	0.50455	0.46991	0.47128	0.48195	0.47416	0.45474	0.47435	0.47096	0.47814	0.47797	0.479
Company ID	4511	4512	4513	4514	4515	46101	4603	4604	4605	4607	4608
$\gamma(U)$	0.5125	0.51883	0.50431	0.51201	0.50526	0.52112	0.50994	0.52176	0.52798	0.52433	0.50513
$\gamma(M)$	0.50298	0.49394	0.48962	0.48226	0.47493	0.50371	0.5027	0.50102	0.50912	0.49701	0.49944
$\gamma(D)$	0.49456	0.4844	0.47616	0.46586	0.46235	0.47547	0.49713	0.47948	0.46159	0.46885	0.49361
Company ID	4701	4702	4703	4705	4706	4707	4801	5001	5004	5005	5006
$\gamma(U)$	0.51747	0.52216	0.54297	0.53149	0.53857	0.51588	0.51498	0.52699	0.51666	0.50321	0.51172
$\gamma(M)$	0.5014	0.50032	0.51154	0.49923	0.49689	0.50474	0.49767	0.49537	0.50421	0.49197	0.49423
$\gamma(D)$	0.48281	0.47635	0.47008	0.47662	0.45274	0.47512	0.47748	0.47472	0.48094	0.4722	0.47556
Company ID	5007	5008	5009	5302	5305	5306	5309	5310	5311	5312	5313
$\gamma(U)$	0.50662	0.50541	0.52716	0.50738	0.50774	0.50697	0.5213	0.50395	0.51026	0.52265	0.50639
$\gamma(M)$	0.49988	0.49351	0.49893	0.50101	0.5013	0.4998	0.50408	0.49493	0.50206	0.49964	0.49993
$\gamma(D)$	0.49397	0.47712	0.46618	0.49379	0.49389	0.49443	0.48012	0.48899	0.49339	0.48518	0.49375
Company ID	5314	5315	5317	5318	5319	5322	5323	5324	5325	5327	5328
$\gamma(U)$	0.50677	0.50815	0.50883	0.50729	0.50568	0.50722	0.50885	0.52135	0.5074	0.5095	0.50986
$\gamma(M)$	0.50033	0.5014	0.50113	0.5003	0.50106	0.49882	0.50063	0.50363	0.49138	0.5026	0.49416
$\gamma(D)$	0.49455	0.49456	0.49534	0.49397	0.49419	0.49293	0.49308	0.48259	0.47471	0.49469	0.48043
Company ID	5332	5333	5335	5336	5337	5342	5344	5345	5347	5351	5352
$\gamma(U)$	0.50742	0.51877	0.51905	0.51678	0.51755	0.50823	0.5112	0.51249	0.5106	0.50748	0.50571
$\gamma(M)$	0.50104	0.50201	0.50044	0.49827	0.49628	0.49322	0.50224	0.49423	0.50183	0.501	0.49961
$\gamma(D)$	0.49465	0.48005	0.4826	0.47737	0.47455	0.47921	0.49462	0.48146	0.49407	0.49349	0.49453
Company ID	5353	5354	5355	5356	5357	5358	5359	5360	5361	5362	5363
$\gamma(U)$	0.50662	0.50652	0.5271	0.50384	0.5205	0.50651	0.51	0.51551	0.50778	0.50972	0.50942
$\gamma(M)$	0.49967	0.50052	0.4895	0.4923	0.4945	0.50044	0.50134	0.5024	0.5004	0.49366	0.5011
$\gamma(D)$	0.49318	0.49326	0.47071	0.47733	0.46896	0.49389	0.49431	0.47555	0.49356	0.47635	0.4939
Company ID	5364	5365	5502	5503	5504	5505	5506	5509	5511	5513	5514
$\gamma(U)$	0.50602	0.50688	0.50655	0.506	0.5172	0.50874	0.51983	0.54323	0.52943	0.50451	0.51146
$\gamma(M)$	0.49993	0.50025	0.50037	0.49355	0.47169	0.49951	0.49398	0.51166	0.48285	0.48645	0.49589
$\gamma(D)$	0.49363	0.49324	0.49286	0.4815	0.45452	0.48953	0.46502	0.46276	0.46351	0.46637	0.4733
Company ID	5603	5604	5605	5701	5702	5810	5817	5818	6001	6003	6015
$\gamma(U)$	0.50425	0.52612	0.52357	0.5084	0.50419	0.50753	0.50572	0.50745	0.50707	0.50769	0.50988
$\gamma(M)$	0.48844	0.50714	0.50054	0.4892	0.49221	0.50104	0.49973	0.50023	0.50041	0.50048	0.50088
$\gamma(D)$	0.46272	0.46546	0.47432	0.4762	0.47063	0.49745	0.49431	0.49564	0.49404	0.49384	0.4955
Company ID	6016	8902	8903	8905	89069	8908	8910	8913			
$\gamma(U)$	0.50746	0.5277	0.51555	0.52798	0.52765	0.53355	0.5328	0.52424			
$\gamma(M)$	0.50063	0.50416	0.4968	0.49157	0.49987	0.50976	0.50019	0.5031			
$\gamma(D)$	0.49425	0.47857	0.47349	0.47179	0.47192	0.457	0.46927	0.47033			

Table 4 reports the estimates for P_i for the 107 stocks in our samples. The number ranges from 0.04 to 0.30 [Note 10]. These estimates serve as proxies for the probabilities of informed trading and will be used in the following market performance tests.

Table 4:
Estimates of the Probability of Informed Trading

P_i for each stock is the average of the P_i's estimated by the bid and the ask price using the method describe in Section 4, which can be done only numerically. These numerical estimates are done in MATLAB [Note 12].

Company ID	4204	4301	4302	4401	4403	4404	4502	4503	4504	4506	4508
P_I	0.30393	0.12973	0.13032	0.13679	0.07554	0.14849	0.07941	0.15135	0.126	0.07027	0.08531
Standard deviation	0.09849	0.04603	0.05034	0.04834	0.02656	0.05252	0.02817	0.05299	0.04455	0.02484	0.03138
Company ID	4511	4512	4513	4514	4515	46101	4603	4604	4605	4607	4608
P_I	0.0642	0.14162	0.6935	0.1029	0.11835	0.09621	0.04741	0.07502	0.22053	0.12968	0.06303
Standard deviation	0.02033	0.04926	0.02716	0.03744	0.0421	0.03478	0.01195	0.02622	0.08579	0.04761	0.02156
Company ID	4701	4702	4703	4705	4706	4707	4801	5001	5004	5005	5006
P_I	0.06349	0.0713	0.17191	0.17895	0.26963	0.12033	0.07257	0.08079	0.08553	0.09147	0.06683
Standard deviation	0.02336	0.02536	0.06153	0.06961	0.08653	0.04403	0.0259	0.02784	0.03097	0.03428	0.02448
Company ID	5007	5008	5009	5302	5305	5306	5309	5310	5311	5312	5313
P_I	0.0604	0.07627	0.08894	0.05605	0.05939	0.04855	0.06767	0.05253	0.05774	0.07732	0.04843
Standard deviation	0.01986	0.02237	0.03034	0.01881	0.01991	0.01338	0.02361	0.0173	0.02015	0.02649	0.01277
Company ID	5314	5315	5317	5318	5319	5322	5323	5324	5325	5327	5328
P_I	0.04775	0.05021	0.05865	0.04953	0.04792	0.05421	0.06005	0.06639	0.06256	0.06037	0.05585
Standard deviation	0.01128	0.01491	0.01935	0.01437	0.01162	0.01704	0.02011	0.02277	0.02127	0.02118	0.01854
Company ID	5332	5333	5335	5336	5337	5342	5344	5345	5347	5351	5352
P_I	0.05688	0.07539	0.05833	0.07348	0.08935	0.05756	0.05349	0.05889	0.04445	0.05098	0.05241
Standard deviation	0.01916	0.02656	0.0189	0.02594	0.03245	0.01927	0.01633	0.01947	0.00902	0.01444	0.01558
Company ID	5353	5354	5355	5356	5357	5358	5359	5360	5361	5362	5363
P_I	0.05131	0.05482	0.15914	0.06243	0.10708	0.04989	0.05254	0.09007	0.05001	0.06356	0.0546
Standard deviation	0.01451	0.0167	0.05597	0.02278	0.03976	0.01271	0.01583	0.03179	0.0137	0.02261	0.01804
Company ID	5364	5365	5502	5503	5504	5505	5506	5509	5511	5513	5514
P_I	0.05166	0.05384	0.06737	0.06696	0.1371	0.06049	0.10784	0.16977	0.2267	0.08038	0.07975
Standard deviation	0.01584	0.01659	0.02291	0.02279	0.05146	0.01755	0.03958	0.059	0.08439	0.0289	0.02849
Company ID	5603	5604	5605	5701	5702	5810	5817	5818	6001	6003	6015
P_I	0.29249	0.15927	0.07592	0.05557	0.08246	0.0491	0.05238	0.0505	0.046	0.04483	0.04774
Standard deviation	0.0883	0.05712	0.02761	0.01771	0.03029	0.01136	0.0135	0.01159	0.00985	0.00819	0.01129
Company ID	6016	8902	8903	8905	89069	8908	8910	8913			
P_I	0.05471	0.0882	0.06416	0.13128	0.13875	0.1862	0.16644	0.1026			
Standard deviation	0.01641	0.03333	0.02387	0.05221	0.04914	0.06622	0.05872	0.03646			

Informed Trading and Stock Performance

In this section, we discuss the interrelation between the probability of informed trading and the liquidity, volatility and efficiency of the stock and establish the structural model for empirical test.

Liquidity and Informed Trading

Kyle (1985) models the process by which information is incorporated into prices when there is monopolistic informed trader, in his model, and many that follow, the informed trader's strategy is a function of the depth of the market. Admati and Pfleiderer (1988) introduce discretionary liquidity traders into the price formation process and propose that informed traders will follow the trading pattern of the uninformed traders whose trades tend to cluster together; in other words, liquidity attracts informed trading. Subrahmanyam (1991) points out that if informed traders are risk averse, the conclusion of Admati and Pfleiderer may not sustain;i.e., higher liquidity does not necessarily leads to more informed trading. On the other hand, Foster and Viswananthan (1990) argue that discretionary uninformed traders will delay their trading when the probability of informed trading is high, in other words, higher probability of informed trading will lead to lower market liquidity. Madhavan (1992) has similar conclusion that depth is a negative function of private information. However, empirical studies of insider trading (e.g., Cornell and Sirri, 1992; Kabir and Vermaelen, 1996) support a positive relation between insider trading and liquidity. To sum up, profit-maximizing informed traders make trading decisions based on the depth of the market, and the latter is also a result of the trading decisions of the informed and uninformed. Both will be taken as endogenous variables in our model, however, the direction of the relation between the liquidity and informed trading needs to be empirically determined.

Efficiency and Informed Trading

In Kyle's (1985) model where there is a monopolistic informed trader, information is released gradually over trading time to maximize the informed trader's profit. From this respect, higher probability of informed trading may lead to less efficient pricing. On the other hand, Holden and Subrahmanyam (1992) modify Kyle's and demonstrate that with competitive informed traders, information will be quickly incorporated into prices and the case is similar to a rational expectation equilibrium. Since the competitiveness of informed traders is not observable, the sign of the relation between efficiency and informed trading can not decide a priori and needs to be empirically determined.

Volatility and Informed Trading

It goes without saying that information leads to changes in prices. But whether volatility induces informed traders to trade? Literature in ARCH models indicates that stock return volatility exhibits clustering phenomena, a possible explanation is that informed trading causes volatility which in turn attracts more informed trading. Foster and Viswananthan (1990) suggest that when public information has some information content, information trading will be high on Monday which leads to high volatility on Monday. Kyle's (1985) model and others that follow all have similar specification that the trading decision of the informed is a function of the volatility of noise trading as well as the volatility of prices. Positive interrelation between volatility and the probability of informed trading is expected in our structural model.

Liquidity, Efficiency and Volatility

A plethora of papers have looked into the relations between volume and prices or volume and volatility (e.g., Karpoff, 1987; Jain and Joh, 1988; Gallant et al., 1992), most find positive relation between the two. Admati and Pfleiderer (1988) also predict that volatility and liquidity are positively related. However, Foster and Viswananthan (1993b) find that for interday data volume and volatility are negatively related. There are less studies dealing with liquidity and efficiency. Grossman and Miller (1988) establish a model for equilibrium liquidity and predict the lower the autocorrelation of returns (i.e., more efficient), the higher is the equilibrium level of liquidity. Amihud and Mendelson (1991) find a positive relation between efficiency and volumes. Others study the relation between information and volatility (e.g., French and Roll, 1986; Jones et al. 1994). To sum up, empirical as well as theoretical researches provide a strong rationale for treating liquidity, efficiency and volatility as endogenous variables in our empirical model.

Before proceeding to the structural equations, we need to define the related measures used in our model. For liquidity measure, instead of the commonly used trading volume, bid and ask order quantities or the number of trades which lead to different results in many of the volatility-volume relation, we use the Amivest liquidity ratio which reflects one concept of depth; i.e., the volume of trades needed to cause a unit change in

Price [Note 11]:

$$LR_{i,t,k} = \frac{\sum_{k=1}^{N} P_{i,t,k} N_{i,t,k}}{\sum_{k=1}^{N} \left|\%\Delta P_{i,t,k}\right|},$$

where $\%\Delta P_{i,t,k} = \left(P_{i,t,k} - P_{i,t-1,k}\right) \big/ P_{i,t,k}$

$P_{i,t,k}$: the stock price of company *i* at trading period *k* of day *t*

$N_{i,t,k}$: the trading volume of company *i* at trading period *k* of day *t*

The larger is the LR_i ratio, the higher is the liquidity for stock *i*.

For volatility measure, we use the standard derivation of returns to measure the interday volatility, as well as the daily price range to measure the intraday volatility; the latter (SP) is as

$$SP_j = \frac{1}{N}\sum_{t=1}^{N} \ln\left(H/L\right)_{jt},$$

where H and L denote the high and low price for stock *i*. *N* is the number of trading periods.

For efficiency measure, we use Lo and MacKinlay's (1988) variance ratios. The variance ratios can be defined for any order great than 1. In this paper, we compute the average of the variance ratios for *q = 1, …, 10*, and define the efficiency measure (*EFF*) as follows:

$$VR_i = \frac{1}{10}\sum_{q=1}^{10} \frac{VR(q)}{q}$$

$$EFF_i = \frac{1}{\left|1 - VR_i\right|}$$

The higher is *EFF*, the more efficient is the stock.

In addition to the above endogenous variables, there are several variables that are used as control variables. For example, ownership concentration is generally considered to be highly related with probability of informed trading and liquidity. Turnover ratios may reflect the degree of informed trading as suggested in some research, or it may represent on the contrary the extent of noise trading. The size of the firm is an important factor to all of the measures. The volatility of stock is usually related with the level of spread and the price of stock. Finally, due to the heat in the hi-tech industry during the study period, a high-tech industry dummy is used.

Now, we can define the structural equations as follows.

$$PI_i = \beta_{10} + \beta_{11}\ EFF_i + \beta_{12}\ LIQ_i + \beta_{13}\ VAR_i + \beta_{14}\ con_i + \beta_{15}\ turn_i + \beta_{16}\ size_i + \mu_1$$
$$EFF_i = \beta_{20} + \beta_{21}\ PI_i + \beta_{22}\ LIQ_i + \beta_{23}\ size_i + \mu_2$$
$$LIQ_i = \beta_{30} + \beta_{31}\ PI_i + \beta_{32}\ EFF_i + \beta_{33}\ con_i + \beta_4\ size_i + ind_i + \mu_3$$
$$VAR_i = \beta_{40} + \beta_{41}\ PI_i + \beta_{42}\ EFF_i + \beta_{43}\ LIQ_i + \beta_{44}\ size_i + \beta_{45}\ spd_i + \beta_{46}\ price_i + \mu_4$$

where

	:	the probability of informed trading of stock *i*
EFF_i	:	efficiency index measure for stock *i*
LIQ_i	:	liquidity index measure for stock *i*
VAR_i	:	volatility index measure for stock *i*
con_i	:	ownership concentration
$turn_i$	:	turnover ratio
$size_i$	:	market capitalization
ind_i	:	industry type; a dummy variable =1 for electronic industry, 0 otherwise
$price_i$	:	average stock price
spd_i	:	average spread

Here, PI_i, EFF_i, LIQ_i, and VAR_i are endogenous variables, and con_i, $size_i$, ind_i, $turn_i$, $price_i$, and spd_i are exogenous variables. μ_1, μ_2, , and are random error terms associated with the structural equations.

Two-stages least squares (2SLS) is first used to estimate the coefficients in the structural equations. We find the residuals associated with each regression equations are highly correlated. Three-stages least squares method is then applied. Since all equations are over-identified, there is gain in efficiency in the estimation of coefficients using 3SLS; See, for example, appendix of chap 12 of Pindyck and Rubinfeld (1998) for more details. The empirical result is reported in Table 5. Most coefficients are significant with p values of 0.01.

Table 5 exhibits the descriptive statistics of the probability of informed trading ranked by trading volumes and market capitalization. The samples are divided into quintiles according to trading volume (in number of shares) or firm size, the first quintile being the firms with highest volume or largest firm size. The simple comparison of means show that the probability of informed trading (P_i) decreases with firm size or trading volume, and the differences are significant. This is consistent with previous findings. However, result of the 3SLS described below reveals a different picture in the relation between firm size and P_i.

Table 5:
The Descriptive Statistics of P_i by Volume and Capitalization

Panel A : Rank by Volume (share)

Note : The joint test (Kruskal-Wallis Test) and the pairwise test (Wilcoxon 2-Sample Test and Kruskal-Wallis Test) are significant at α= 0.01 for all comparisons, indicating that P_i's are significantly different among volume quintiles.

Panel B : Rank by Capitalization

Note : The joint test (Kruskal-Wallis Test) and the pairwise test (Wilcoxon 2-Sample Test and Kruskal-Wallis Test) are significant at α= 0.01 for all comparisons, indicating that P_i's are significantly different among size quintiles.

Table 6 reports the regression result of the 3SLS. We find that P_i and the volatility and liquidity of stocks are simultaneously determined. Higher P_i leads to lower liquidity and higher volatility, and vice versa. This finding is consistent with Foster and Viswananthan's (1990, 1993a) argument that informed trading reduces liquidity, but it does not support Admati and Pfleiderer's (1988) prediction that liquidity attracts informed trading. Our finding also provides support to Kyle's (1985) model that informed trading is a positive function of the volatility of noise trading. On the other hand, P_i and efficiency do not appear to have two-way connections. The probability of informed trading increases with the efficiency of the stock, while higher P_i does not leads to greater efficiency. Our finding suggests that Kyle's (1985) non-competitive informed trader model explains better the price discovery process in Taiwan OTC Stock Exchange than Holden and Subrahmanyam's (1992) competitive informed traders model.

Table 6:
Result of 3SLS Regression Model

is the probability of informed trading of stock i, EFF_i is the efficiency measure, LIQ_i is the liquidity measure, VAR_i is the volatility measure, con_i is the ownership concentration, is the turnover ratio, is the market capitalization, ind_i is a dummy variable=1 for electronic industry, 0 otherwise, is the average stock price, is the average spread.

Dependent variable	Independent variable	*VAR* = *SP*	*VAR* = Standard deviation
PI	*EFF*	.0152083*	0.00726396*
	LIQ	(-0.0210366)*	(-0.0209891)*
	VAR	20.6053	33.6957*
	con	0.000584634*	0.000236018*
	turn	(-0.000102395)*	(-0.0000881168)*
	size	0.0396415*	0.015396*
EFF	*PI*	3.903	0.237418
	LIQ	0.0938753*	0.0401138*
	size	-0.0482677	0.087259
LIQ	*PI*	(-8.8921)*	-2.35646
	EFF	-0.0059994	-0.00156
	con	(-0.00475679)*	(-0.0127537)*
	size	1.88589*	1.83781*
	ind	0.156165	0.379666*
VAR	*PI*	0.00525382*	0.0160389*
	EFF	0.000205337*	(-0.000135917)*
	LIQ	0.000254726*	0.000509766*
	size	(-0.000121837)*	(-0.000120272)*
	spd	0.00251795*	0.0148482*
	price	(-0.0000518576)*	(-0.00018299)*

*indicates significant at level 0.1, the coefficients on column 3 (4) is the result when SP (standard deviation of return) is used to measure volatility.

As to the interrelations between liquidity, volatility and efficiency, the interesting finding is that liquidity can explain volatility and efficiency, while the opposite is not true. It seems to suggest that liquidity is the dominant performance factor over the other two. In other words, our result does not support Grossman and Miller's (1988) argument that the equilibrium level of liquidity is affected by the autocorrelation of returns. The result also shows that efficiency is negatively related with interday volatility but positively related with intraday volatility, indicating more efficient stock has higher intraday volatility, but information is quickly incorporated into prices by the end of the day so that interday volatility is smaller for more efficient stocks.

In terms of the exogenous factors, we find that firms with larger size, higher ownership concentration and lower turnover have higher probability of informed trading. It is interesting to see that, after controlling for other factors, the negative relation between firm size and P_i observed in Table 5 turns into positive in Table 6. This suggests that previous studies which conclude a negative relation between firm size and P_i by a simple comparison of means may be questionable. It is also interesting to see that turnover ratio is negatively related with informed trading, suggesting turnover ratio is a noise trading index in Taiwan.

Policy Implications and Conclusions

In this paper we estimate the probability of informed trading P_i for individual stock traded in the order-driven Taiwan OTC market by modifying Easley, Kiefer and O'Hara's (1997b) model and using a different estimation technique. In addition, unlike previous empirical studies we examine comprehensively the interrelations among informed trading, liquidity, efficiency and volatility using a system of equations approach that takes into consideration the endogeneity of these variables.

Consistent with our trade model assumption of the behavior of the uninformed traders, our finding indicates that uninformed traders exhibit price chasing behavior even over very short interval, and they tend to buy when the price in the previous trading period goes up and sell when the price in the previous trading period declines. We also find that volatility in prices attracts noise traders to trade. Uninformed traders are more likely to trade when price moves in the previous trading interval. This finding suggests that a temporary trading halt mechanism may indeed be warranted to reduce excess volatility.

We also find that high P_i leads to lower liquidity and higher volatility, and vice versa. This finding supports Foster and Viswananthan's (1990) argument that informed trading reduces liquidity but is contrary to Admati and Pfleiderer's (1988) prediction that liquidity attracts informed trading. In terms of policy implication, our finding suggests that the popular trend in exchanges around the world to enhance pre-trade transparency may actually lead to undesirable result, that is, lower liquidity and higher volatility, if the market is not large enough.

In addition, we find no evidence that higher probability of informed trading leads to higher efficiency. One possible explanation is that the samples in this study are firms listed in the Taiwan Gre Tai Exchange, where the firm's sizes are smaller and the trading volumes are also lower than those listed in the Taiwan Stock Exchange. Therefore, informed traders in these stocks are much less competitive. As suggested by Kyle (1985), when there is monopolistic informed trader, the price discovery process is slower given the profit maximizing behavior of the monopolistic informed trader. Our finding that high probability of informed trading does not lead to more efficient pricing for stocks listed in Taiwan Gre Tai Exchange illustrates the importance of competition to market efficiency, that is, informed trading alone does not lead to efficiency.

Unlike Hasbrouck (1991b) and Easley et al. (1996) who found that firms with larger size have *lower* P_i, we find that, after controlling for other factors, firms with larger size have *higher* P_i , and that ownership concentration and lower turnover lead to higher P_i. These results have interesting implications for uninformed traders. High turnover is often attributed to informed trading in the U.S. market where institutional investors dominate. On the contrary, our study finds that, in a market dominated by individual investors as in most Asian stock markets, high turnover implies high percentage of noise trading. The uninformed would have lower chance of trading with the informed (usually the institutional investors) by avoiding large firms and firms with low turnover ratios.

Notes

1. A number of studies explore the components of bid ask spreads and estimate the adverse selection component of spreads, e.g., Glosten (1987), Glosten and Harris (1988), Stoll (1989), and George et al. (1991).
2. While most studies confirm the negative relation between firm size and the probability of informed trading, the empirical evidence on the relation between trade size and informed trading is mixed. Easley, Kiefer and O'Hara (1997b) show that larger trade size tends to have higher information content. Keim and Madhavan (1996) find that block price impacts are a concave function of order size. Barclay and Warner (1993) on the other hand find informed traders are more likely to concentrate on medium-size orders.
3. Handa et al. (2003) and Chou and Handa (2000) are rare examples of studies on the order-driven market, however, their focus was in the estimation of spread components rather than the probability of informed trading.
4. In order to estimate the likelihood function in EKOP-type model, one needs the assumption of independence across days. Although Easley et al. argue that in an earlier 1993 paper they have tested the independence of information events across days and can not reject the independence assumption, we find it hard to justify that number of buys and sells are not dependent over time.
5. For example, Kyle (1985), Grossman (1988), Holden and Subramanyam (1992), Foster and Viswananthan (1990, 1993a) and Admati and Pfleiderer (1988) discuss the theoretical implications between informed traders, liquidity and efficiency, while Cornell and Sirri (1992), and Kabir and Vermaelen (1996) empirically examine the relation between insider tradings and liquidity.
6. For example, Kyle (1985), Admati and Pfleiderer (1988) both propose that liquidity attracts informed traders to trade.
7. Another possible explanation is heterogeneity of information – Back, Cao and Willard (2000) show that if the correlation of information among traders is low, the relationship between market efficiency and informed trading is more complicated.
8. The sample in this study are firms listed in the Taiwan OTC Exchange, which is a liquid market for smaller firms (though there are some large firms listed too), otherwise the trading mechanism is the same as the Taiwan Stock Exchange
9. See Sentana and Wadhwani (1992) for empirical evidence on the positive feedback behavior.
10. Compared with Easley et al. (1996), the mean arrival rate of informed is between 0.015 to 0.13
11. Amihud, Yakov (2002), for example, used the ratio to measure liquidity in their study.
12. MATLAB is scientific computation software and a trademark of The MATHWORKS Company.

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