Price Formation in a Market with a Short-Sale Prohibition: an Empirical Investigation

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This study examines the behaviour of stock prices in the presence of asymmetric information, when market participants are prohibited from short selling. Although insiders privy to negative information may not exploit this information by selling if they do not own the stock, the market maker can deduce the occurrence of bad news by observing the trading patterns. Previous work indicates that good news is associated with high volume and bad news with low volume, and that the speed of price adjustment is greater on bad news than on good news. This result depends upon parameters determining the structure of the market in terms of the types of participants (informed or uninformed) and their relative holdings of the stock. The conclusions are tested by an empirical study of stocks trading on the Stock Exchange of Thailand, where short sales are prohibited. The empirical results are used to verify the theory and also to examine the composition of the Thai market by estimation of the relevant parameters.

August, 2000

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Inside information and restrictions on trading opportunities are generally considered to be detrimental to market efficiency. Market makers react to these conditions as they attempt to set prices and quote spreads for their stocks. Their decisions to adjust their prices and spreads are based on observation of the orders they receive from traders who cannot be identified as having superior information or not. Both the type of orders, as buys or sells, and the volume of trading, either per order or in aggregate, are partially revealing of the true nature of information in existence. In addition, the absence of orders potentially signals the occurrence of news. If short selling is prohibited, then informed traders aware of bad news will only be able to sell if they already own stock in sufficient quantity to satisfy their desire to profit from the news. Hence the observation of no trades may be indicative of the presence of informed would be sellers. The market maker's problem is lessened if he has a good idea of the percentage of traders in the stock who are informed and of the holdings of informed and uninformed investors in the stock. With this information, better estimates can be made of the probabilities that buys, sells and no trades are being generated by either informed or uninformed traders.

Academic literature contains numerous attempts to provide structure to this problem as part of market microstructure. Kyle [1985] analysed order flow in continuous time to show that information is gradually incorporated into prices over time as informed traders could generate more profits from continuous trading than strategic entries. Foster and Viswanathan [1990] modified this approach and found a relationship between size of orders and the activity of a monopolist insider, with the result that the uninformed could gain information from observing the trade history. Glosten and Milgrom [1985] created a sequential equilibrium model with prices equal to the market maker's conditional expectation of asset value based on trade flow, finding volume not to be increasing in the variance in prices. Diamond and Verrecchia [1987] extended Glosten and Milgrom's model to include three types of short sale constraints. They examined whether market short sale constraints affect the trading propensity, thereby causing asymmetries in the speed of price adjustment to good and bad news. They concluded that a short-sale prohibition reduced the speed of price adjustment to inside information.

Easley and O'Hara [1987] used a modified, discrete time Glosten and Milgrom approach to include different trade sizes and information uncertainty. The market maker attempted to determine both the existence and direction of new information. Easley and O'Hara [1992a] focused on the trade process instead of the usual price process, finding that 'event uncertainty' provides an informational role for trading volume gained directly from the properties of the underlying information structure, with time and volume becoming endogenous variables. By opening the possibility of a 'no trade' event to all agents, the model predicts the positive correlation between price observation and trading volume. Easley, Kiefer and O'Hara [1995] and Easley, Kiefer, O'Hara and Paperman [1996] proposed empirical studies based on the Easley and O'Hara [1992a] paper, with the latter study moving to continuous time. Brennan and Subrahmanyam [1995a] found that privately informed investors create significant illiquidity costs for uninformed investors, while Foster and Viswanathan [1995] found a model of speculative trading to be partially consistent with the asymmetric volume-volatility relationship, as evidenced by intraday transaction data for an individual firm during 1988.

In a previous paper (1999), the authors of this study presented an analysis based on the Easley and O'Hara (1992a) model (henceforth EO); that analysis modelled the short selling prohibition and showed it to lead to reduced volume on selling associated with bad news in comparison to increased volume on buying associated with good news. We also showed how the lower volume associated with bad news made a speedy adjustment of the price to the decreased equilibrium value, a relatively efficient price revision compared to the good news case. The conclusion depends on some of the parameters of the model, but the indicated value ranges are reasonable and have logically consistent limiting cases. The prediction of a faster adjustment is tested by examination of data drawn from the Stock Exchange of Thailand (SET). The later works of Easley, Kiefer and O'Hara (1995) and Easley, Kiefer, O'Hara and Paperman (1995) (referred to as EKO and EKOP, respectively) are used as a basis for estimation of the model parameters; these parameters inherently describe the composition of the market and the release of information, such as the percentage of informed investors, the stock ownership of informed and uninformed investors, and the likelihood of good or bad news.

In the next section, we shall describe the model and notation, and present the statistical concept of entropy for measuring the convergence of distributions. Following that, we shall summarise the theoretical results concerning speed of convergence of the estimated price distribution to the true distribution known only to informed investors. In the subsequent section, we explain the testing procedure by which we examine intra-day trading data for confirmation of the predicted convergence result; a number of hypotheses are made as to the revealed structure of the market in which the participants trade on the SET. Following this, we present the results of those tests and the estimates of parameters. Finally, we discuss inferences based on the conclusions of empirical investigation and summarise our results.

1. Introduction to the Model and Parameters

We assume a single risky asset traded without transaction costs in a pure and competitive dealership market in a single period, divided into equal-length trading intervals. The market has three types of risk-neutral participants: informed traders or insiders, uninformed liquidity traders, and market makers. At the beginning of each trading interval (t=0) informed traders observe privately a signal Θ[1], perfectly correlated with the true value of the risky asset. Let ∀0(0,1) denote the probability of an informational event occurring. The informed trader will use the private information to buy if the asset is underpriced and sell all owned shares if overpriced. The asset is overpriced (underpriced) if its asking price is more (less) than the trader's conditional expectation of its liquidating value given the signal Θ. An informed trader will not trade in the absence of information or the lack of stock to sell.

Second, we have the liquidity traders, who are price takers and uninformed about Θ. They trade in the risky asset for exogenous non-informational reasons or portfolio considerations (consumption needs, tax planning, etc.), selling and buying randomly, with respective probabilities (and 1-(. Finally, market makers are uninformed about Θ, or about the future value of the risky asset. Each market maker[2] sets prices at which he will be ready to buy

[1] The extensive notation is summarised in Table 1.

[2] For simplicity, we refer to the actions of a single market maker, but the assumption of competitive behaviour requires the existence of at least one potential competitor. For a complete description of the behaviour of the market maker see the preceding paper by the authors.

or to sell with any traders for at most one unit of the traded asset at any time, based on observation of the order flow from traders unidentifiable by him.

Each trading day is divided into n equal discrete time subdivisions, denoted by t=1,...,n. The signal Θ is observed by the informed traders at some time prior to t=0.The trading interval is designed to be sufficiently small as to include at most one trade, with the result that no trade may also occur. Hence, at each subdivision we observe one out of three mutually exclusive events, drawn from the set {B,S,N}, for buy, sell and no trade.

In accordance with EO, the model assumes that the market maker chooses randomly either an informed or a liquidity trader from the population of all traders, with respective probabilities Φ and $1-\Phi$, where $\Phi 0(0,1)$.[3] Both types of traders choose their strategies from the set {B,S,N} when trading with the market maker. Whenever the chosen agent does not own the asset, a desired sell order is replaced by a no trade. We denote by h_I and h_U the respective probabilities that informed and uninformed traders own the asset, where $h_j 0(0,1)$ for j=I,U; thus an N outcome occurs with probability $1- h_j$ if the selected trader wishes to sell but does not own the stock. By contrast, an N outcome cannot result from any trader wishing to buy. This asymmetry between buys and sells causes the results of this model to differ from those of EO.

Neither market maker nor uninformed traders knows if the informational event Θ has occurred or, if it has, whether it is "good news" or "bad news". All agents know the structure of the economy. Figure 1 summarises the tree diagram of the trading process induced by the model.

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[3] μ, unlike the other parameters, cannot be 0 or 1, because then market makers will almost certainly learn the value of Θ in finite time; see Easley and O'Hara (1992a, p.595, note 14).

(Figure 1 about here)

In the absence of an informational event, the eventual value of the risky asset is a universally known random value V per share, with positive mean and variance. When an informational event occurs, observed only by the informed traders, the signal Θ is given, which is low with <u>prior</u> probability ∗ or high with probability 1-∗, where ∗0(0,1). We characterise the signal then by Θ={L,H,0}, where L (H) denotes that the risky asset has low (high) value and Θ=0 denotes the event of no information. Let also V_L/E{V*Θ=L} and V_H/E{V*Θ=H} denote the conditional expectations given that the indicated informational event has occurred. By contrast, for Θ=0 the unconditional expected value of the asset is given by V*=∗V_L+(1-∗)V_H; hence V_H>V*>V_L.

We also examine the relative speed of adjustment of the stock price as it converges to the value V_H or V_L, whichever is perceived to be true. In order to measure the speed of convergence, we use the statistical concept of *entropy*.[4] Entropy is a conceptual measure of the uncertainty of a random variable. One can interpret entropy as the expected value of the natural logarithm of the inverse of the probability of a random variable. In this case, the uncertainty is in the market maker's belief about the true state of nature described by the existence and type of signal that has occurred. The *relative entropy* is defined as a measure of the 'distance' between two probability distributions. Mathematically, the relative entropy of $P^{\Psi'}$ under P^{Ψ} is defined as:

$$I_{P^y}(P^{y'}) = \Sigma \quad P^{\Psi}(Q)\ \ln [\, P^{\Psi}(Q) / P^{\Psi'}(Q)\,] \qquad (1)$$

4 Entropy was suggested by Easley and O'Hara [1992a] for this purpose; we extend their notion here by deriving the actual measures and comparing them under the different informational alternatives.

$Q \in \{N,B,S\}$

This expression is used frequently in information theory due to its mathematical properties. By assuming the distribution of $P^{\psi'}$ when the true distribution is P^{ψ}, one can measure the relative distance or convergence between the two probability distributions over the sequential trades. The relative entropy is thus a measure of the inefficiency of that assumption and provides the rate of exponential convergence of probabilities and prices to their limits, which are presumed to be the true values.

2. The Effect of Short Sales Restrictions on Price Adjustment

In the earlier paper, we proved that the market maker could conclude the existence of an information event from observation of the trading process, as measured by the aggregate numbers of buys, sells and no trades to date. An unexpectedly large number of no trades could be used to infer the occurrence of bad news that was causing informed investors who did not own the stock to refrain from trading, while those who did own stock would issue sell orders. While the stock price adjusted to its new equilibrium price, low volume would be observed as it fell in contrast to higher volume on increases in the price. Volume is defined as the sum of buys and sells over the trading period. Given the construction of the trading intervals, we have after t periods the relationship $t = \boldsymbol{b}_t + s_t + n_t$; then the volume over the trading period is $v_t = \boldsymbol{b}_t + s_t = t - n_t$. The conclusive result depended on the parameter value for the occurrence of bad news, as stated in the following theorem, proven in the earlier paper.

Theorem 1: If δ is less than or equal to ½, then there exists a positive intertemporal relationship between observed trading volume and expected future stock price above a certain value of the trading volume, i.e. $E[V_{t+1} | v_t=j]$ is increasing in j above a certain value of j.

In deriving the results, we found a crucial condition on what we identify as the propensity to short sell. Short selling by uninformed investors occurs only if they wish to sell and have the stock, measured by $(1- h_U)\ \gamma$; for informed investors, the wish to sell is not probabilistic but determined by news, and hence occurs if they own the stock. We then required that the propensity of uninformed investors to short sell be less than the corresponding propensity for informed investors, or

$$(1- h_U)\, \gamma < (1 - h_I) \tag{2}$$

This condition requires initially that $h_I < 1$, which is necessary for the proof of Theorem 1, as it ensures that the prohibition on short sales is effective on some informed investors. This short sale prohibition effect on the price-volume relationship is at odds with He and Wang [1995], who found that private information, both good news and bad news, not only generates trading in the current period, but also leads to possible trading in a future period.

One may conjecture that the lower volume adjustment of the price on bad news occurs by larger and thus faster moves downwards than the slower, more gradual, but more highly liquid trading that moves the price up on good news. This is not necessarily the case, however; trading on bad news could occur as a discontinuous, infrequent pattern of trades. Whichever might be the case may well depend upon the composition of the market. By characterising the trading pattern further, and basing the pattern on the proportions of types of traders and their stock holdings, we are able to generate some testable implications.

The use of entropy to measure the exponential convergence is only valid for a Markov process, which applies to the distribution of the variables $(b_{t+1}, s_{t+1}, n_{t+1})$. The entropy lies between the true distribution and any alternative distribution for the trade statistics. The observed proportions of trades, which are the posterior distributions, would converge almost surely (a.s.) to the true equilibrium values according to the Strong Law of Large Numbers. Since the equilibrium price is a linear function of the market maker's revised probabilities of the terminal values, the price would converge a.s. to V_ψ at the exponential rate determined by the minimum of $I_P{}^{\Psi}(P^0)$ and $I_P{}^{\Psi}(P^H)$ for ψ = L, H.

Proposition 1: Transaction prices, converge to their strong form efficient values at exponential rates. If signal ψ occurs, the exponential rate of convergence is:

$$r(\psi) = \text{Min.}\ \{I_P^{\psi}(P^{\psi'}): \psi \neq \psi'\},$$

where $I_P^{\psi}(P^{\psi'})$ is the entropy of $P^{\psi'}$ relative to P^{ψ}. $I_P^{L}(P^{O})$ and $I_P^{H}(P^{O})$ are the minima for ψ = L and H.[6]

The proposition states that in the 'good' news or high signal case, the exponential rate of convergence is $I_P^{H}(P^{O})$, since it is less than $I_P^{H}(P^{L})$. For the 'bad' news or low signal case, the rate of convergence is $I_P^{L}(P^{O})$, as it is less than $I_P^{L}(P^{H})$. Note that if h_U = 1 or 0, the results are indeterminate; if all or none of the uninformed traders own the stock, the market maker can deduce the signal occurrence in finite time (a.s.). For that reason, the speed of adjustment would explode, as the market price would converge immediately to the true value. A more detailed analysis indicates that both minima $I_P^{H}(P^{O})$ and $I_P^{L}(P^{O})$ from Proposition 1 are sensitive to the variation in γ and μ, as shown in Figures 2 and 3. In fact, both convergence rates are increasing monotonically in μ and γ. As the probability of informed trader participation increases, the speed of convergence increases; the market maker learns the 'bad' news faster when confronted by numerous insiders subject to short sale constraints. (In reality, a high fraction of insider ownership is likely to be true in entrepreneur dominated business environments, as found in emerging markets such as Thailand).

(Figures 2 and 3 about here)

[6] For ψ = 0, the minimum rate of convergence is parameter dependent. For γ = 1/2 as our benchmark case, however, the minimum rate is $I_P^{0}(P^{H})$ for all other parameter values. The proof is not included in the

The major result is that the market maker will adjust his price downward faster in the 'bad' news case, as he increases his belief that the trade originated with an insider. Consequently, when associated with lower trading volume in the low signal, prices can be expected to adjust at a higher speed than in the case of a high signal, on high volume. This is formalised in the following proposition, where the rate of convergence in the case of a low signal is compared to the rate for a high signal.

Proposition 2: In general, the rate of convergence of quoted prices is parameter dependent. Should uninformed investors be equally likely to buy or sell, however, then without restricting other parameter values, the convergence rates for ψ = L and ψ = H are equal in the case of $h_I = h_U$ but faster for ψ = L, in the case of $h_I \neq h_U$. That is, if $\gamma = 1/2$, then

$$\text{Min.}\ \{I_P^L(P^O), I_P^L(P^H)\} = \text{Min.}\ \{I_P^H(P^O), I_P^H(P^L)\} \quad \text{for } h_I = h_U \qquad (3)$$

and

$$\text{Min.}\ \{I_P^L(P^O), I_P^L(P^H)\} > \text{Min.}\ \{I_P^H(P^O), I_P^H(P^L)\} \quad \text{for } h_I \neq h_U \qquad (4)$$

Some explanation of the parameter values is warranted. The standard assumption in previous studies is $\gamma = 1/2$, or that the uninformed is as likely to be a buyer as a seller. The proposition states that in this case, the rate of convergence, $I_P^L(P^O)$, in the 'bad' news case is faster than $I_P^H(P^O)$, the rate in the 'good' news case for $h_I \neq h_U$. When $h_I = h_U$, the two convergence rates are equal; that is, the market makers learn less from the trade process in the unlikely event of equal proportions of informed and uninformed traders owning the stock. The convergence result in Proposition 1 still holds if the majority of uninformed want to *buy* (i.e., $\gamma \leq .5$) as depicted in Figure 4a; however, the inequality can be easily inverted in most cases when

appendix, but is available from the authors on request.

the majority of uninformed want to *sell* (i.e., $\gamma > 0.6$). The conclusion of Proposition 1 is robust relative to other parameter values (i.e., μ, h_I and h_U) when varying one parameter and holding the other parameters equal to one half, as shown in Figure 4b. When $h_U = 1$ or 0, the result is indeterminate, as was the case in Proposition 1. One may hypothesise that the degree of ownership is irrelevant in nearly all cases, unless the market maker knows with certainty whether the uninformed own the stock or not.[7] Hence, we claim that the speed of adjustment in the downward case is faster than in the upward case.

(Figures 4a and 4b about here)

The low signal case is, of course, the most important one, as it is the inability of the informed trader to profit from the privately observed signal that causes the asymmetry in trading. For that reason, we have investigated the reaction to a low signal as a function of the relative holdings of informed and uninformed investors. The results are summarised in:

Proposition 3: The rate of convergence for $\Psi = L$ is dependent on the relative levels of h_I and h_U. Specifically:

i) The rate of convergence is minimised for $h_I = h_U$.

ii) The rate of convergence is infinite for $h_U / h_I = 0$ or $(1- h_U)/(1- h_I) = 0$; that means that when $h_I \neq h_U$ and $h_U = 0$ or 1, the low signal is instantaneously recognised, as uninformed investors can always sell if present in the market.

[7] In fact, in the 'good' news case, $I_P^H(P^O)$ is independent of the value of the h_I parameter.

iii) The rate of convergence decreases monotonically as h_U increases for h_I at its upper boundary of $1 - (1- h_U)\,\gamma$ [8]; hence, for low values of h_U, the fastest convergence occurs for high values of h_I.

iv) The rate of convergence increases monotonically as h_U increases for $h_I = 0$; hence, for high values of h_U, the fastest convergence occurs for low values of h_I.

The subject of the short sale restriction is a controversial one. One argument is that a short sale restriction is needed to prevent informed traders from abusing their material informational advantage over the uninformed traders. Another argument is that the short sale restriction may affect the information efficiency in the market because constraining pessimists without constraining optimists imparts an upward bias to stock prices as suggested by Miller [1977] and Figlewski [1981]. As a result of the above findings, we infer a positive effect from the prohibition of short sales.

Theorem 2: In general, the imposition of a short sale prohibition improves the informational efficiency of the market by expediting the convergence of a stock price to its equilibrium value when $\psi = L$ and leaving it unaffected when $\psi = H$.[9]

The short sale prohibition does not affect the trading behaviour of informed traders when the signal is high, but does prevent some informed traders' selling activities in other cases. With the prohibition, the market participants learn the 'bad' news faster, particularly from 'no trade' events. Proposition 2 and Theorem 2 indicate that the short sale prohibition promotes

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8 The boundary is defined by the condition $(1- h_U)\,\gamma < (1 - h_I)$.

9 For $\psi = 0$, the speed of convergence is faster when a short sale constraint exists and $\gamma = 1/2$. The proof is not shown in the appendix, but is available on request.

market efficiency. Provided the parameters of the market composition are consistent with our conditions, we should expect to see the faster adjustment on bad news reflected in actual trading. We examine this in the final section, where we also investigate the revealed parameters, by estimation from trading history on the SET.

3. Design of the Testing Model

3.1 The Statistical Estimator

The results derived for price formation follow a structural model describing the stochastic trade process shown in Figure 1. The structure and parameters {α, δ, μ, γ, h_I and h_U} of the market are assumed known to all participants, but the market maker knows neither the identity of traders nor the occurrence and nature of an information event. After observing trade flows over time, the market maker updates his beliefs by Bayesian revision. He will then adjust his quotes and thus market *prices* from the trade history.

In developing the theoretical model in the previous paper, we showed that the observable trade-tuples {buys, sells and no-trades} provide sufficient statistics for the determination of the price process. Consequently, one can estimate the parameters (α, δ, μ, γ, h_I, h_U) from the trade-tuples of the trade process. As specified by the model definition and trading tree, the nature of information events (which involve α and δ) in the economy are revealed only once a day, while the trader characteristics (μ, γ, h_I and h_U) are revealed for each and every trading interval throughout the trading day, by the selection of the specific trader.

The implications of having the two different periods for the estimation of the underlying parameters are discussed in EKO section 3. The prevailing parameters can be considered as independent draws from the population. In any trading day, many trade outcomes can be realised; each observation depends on μ, γ, h_I and h_U, but they share a single draw of α and δ, made for that day. Hence, a single day sample of an individual stock is required for the estimation of μ, γ, h_I and h_U, while multiple days of data are needed for α and δ. Although a sufficiently large sample from multiple days is needed to estimate α and δ, it is inappropriate to estimate the remaining parameters on the same basis, as there is a possibility that the market composition of traders may change over time.

We shall use the likelihood function to estimate the parameters, based on examination of the probabilities of the trade outcomes given that ‘bad news’, ‘good news’ or ‘no news’ has occurred on a particular day. Since each trade is independent and drawn from an identical distribution by assumption, it can be shown that the standard estimation problem requires only the total number of buys (B), sells (S) and no-trades (N) to provide sufficient statistics for any given day. The probabilities of buys (B), sells (S) and no-trades (N) on a ‘bad’ news, ‘good’ news, or no news day are given respectively by:

$$\Pr.\{B,S,N \mid \psi=L\} = [(1-\mu)(1-\gamma)]^B\,[\mu h_I + (1-\mu)\,\gamma h_U]^S\,[\mu(1-h_I) + (1-\mu)\gamma(1-h_U)]^N \quad (5)$$

$$\Pr.\{B,S,N \mid \psi=H\} = [\mu + (1-\mu)(1-\gamma)]^B\,[(1-\mu)\gamma h_U]^S\,[\mu(1-h_I) + (1-\mu)\gamma(1-h_U)]^N. \quad (6)$$

$$\Pr.\{B,S,N \mid \psi=0\} = [(1-\gamma)]^B\;[\gamma h_U]^S\;[\gamma(1-h_U)]^N. \quad (7)$$

Equations (5), (6) and (7) represent the conditional likelihood of buys, sells and no trades on known days. Define the vector $\mathbf{Q} = \{\alpha, \delta, \mu, \gamma, h_I, h_U\}$ as the unknown population parameters to be estimated. We can then find the unconditional likelihood for a single day, by multiplying equations (5), (6) and (7) by the probabilities of the news event occurrences, respectively α (1-δ), $\alpha\ \delta$ and (1-α):

$$\begin{aligned}\Pr.\{B,S,N \mid \mathbf{Q}\} &= \alpha\,(1-\delta)\ \{\ [\mu + (1-\mu)(1-\gamma)]^{B}\ [(1-\mu)\gamma h_U]^{S}\ [\mu(1-h_I) + (1-\mu)\gamma(1-h_U)]^{N}\ \} \\ &+ \alpha\ \delta\ \{\ [(1-\mu)(1-\gamma)]^{B}\ [\mu h_I + (1-\mu)\ \gamma h_U]^{S}\ [\mu(1-h_I) + (1-\mu)\gamma(1-h_U)]^{N}\ \} \\ &+ (1-\alpha)\ \{\ [(1-\gamma)]^{B}\ \ [\gamma h_U]^{S}\ \ [\gamma(1-h_U)]^{N}\ \}. \qquad (8)\end{aligned}$$

Since individual trades and successive trading days are independent by the assumption, the conditional probability of observing a sequence of trades over multiple days is the product of the likelihoods, as in EKO (equation 14):

$$\Pr\{\ (B_d\ ,S_d\ ,N_d\ )\ d=1,\ldots,D\ \mid \mathbf{Q}\} = \prod_{d=1}^{D}\ \Pr\{(B_d,S_d,N_d) \mid \mathbf{Q}\} \qquad (9)$$

where (B_d,S_d,N_d) are the outcomes on day d, d =1,...,D, and mutual independence of the information governed by α and δ is assumed.

For a set of observations $\{B_d,S_d,N_d\}$, the specification in the econometric model in (7) becomes a bi-linear 'likelihood' function of α and δ for a single day equivalent to a Bernoulli probability from a single draw. This would not give satisfactory results for estimating α and δ. Instead, the 'likelihood' function for a multiple-day period is then transformed into the log function as follows:

$$\begin{aligned}\boldsymbol{L}\,(\mathbf{Q}) &= \ln \Pr\{\ (B_d\ ,S_d\ ,N_d\ )\ d=1,\ldots,D\ \mid \mathbf{Q}\} \qquad (10) \\ &= \sum_{d=1}^{D} \ln \Pr\{\ (B_d\ ,S_d\ ,N_d\ )\ \mid \mathbf{Q}\}\end{aligned}$$

To estimate the parameter vector **Q** from a set of the data, this log function ***L* (Q)** is maximised.

Volume Decile Portfolios: A total of 3,855,127 observations of transactions data[10] were collected from the SET covering the period from January 3, 1996 to June 13, 1996, giving a total of 102 trading days. The total number of traded securities is 537, of which 69 are listed mutual funds and 32 are warrants. We excluded from considerations all mutual funds, warrants, long-suspended trading securities[11], newly listed securities and rights issuing securities transactions. We further eliminated another 33 stocks which have their own warrants listed in the market, since the presence of the derivative security will distort the trading patterns in the primary security. The opening trades are omitted from the sample as suggested by EKO (section 4). In summary, the data has been refined to 2,138,186 transactions records or about 55.5 percent of the original data.

Subsequently, the remaining 342 stocks are ranked by decile according to their total trading volume, measured as the total number of shares traded during the entire sampling period. By construction, the first (tenth) decile contains the most (least) actively traded stocks from Table 2a. Trading volume decreases dramatically across deciles, the first decile having an average stock trading volume of 791,100 shares per day in contrast to 25,100 shares per day in the fifth decile and 5,681 shares per day in the eighth decile. More than 30% of the stocks in the last decile are traded less than 25 days in the whole 102 day period in contrast to the first decile stocks, which were traded on nearly all trading days. Indeed, the first decile consisted of

10 We are grateful to National Finance and Securities (Public) Ltd., Bangkok Thailand for assistance in data collection.

11 Two stocks officially suspended from trading for more than ten trading days in the sample period were excluded.

more than two-thirds of all market trading activities, and thirty times the volume of the fifth decile, while the remaining volume from the fifth to the tenth decile represents merely 4.43% of market activity. While the average market capitalisation for the first decile is about 36 billion baht in contrast to only 3.94 billion baht for the fifth decile, average prices for the two deciles are relatively comparable. With activity fairly concentrated in the first few deciles, this study focuses on the first and fifth decile portfolios, similarly to the procedure of EKOP.

EKOP constructed a selective matched sampling of stocks having the comparable share prices in different decile portfolios to avoid biases against lower priced stocks, which are normally associated with higher capitalisation. The comparable share price selection, calculated from the average closing price for the period, is meant to eliminate the tick size and price clustering biases found by Harris [1991, 1994].[12] These biases may occur because the tick size between bid and ask is fixed arbitrarily around the stock price in the Thai market[13] and the SET may be prone to these deficiencies as shown by Hoontrakul [1995a, table 1]. Due to data scarcity, however, the first and fifth deciles are ranked merely according to trading volume without the luxury of matched pair stocks, as displayed in Table 2a. Also, the tenth decile would be considered as inactive or composed of low volume stocks rather than medium volume stocks as in EKOP, primarily due to characteristics of the SET

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[12] See Seppi [1996] for discussion on the relation between tick size and liquidity and between the institutional preference and tick size; see also reviews on the discreteness issue by Hasbrouck [1995, pp. 39-43]

[13] See Angle [1996] for more discussion on nontrivial relative tick size and supply liquidity to a small-capitalisation security market **.**

High and Low Volume SET- 50 Portfolios: The 50 stocks constituting the SET 50 index[14] are used to check for the robustness of the results. The 'unusual stocks' defined above were also screened from the SET portfolio. As a result, a dozen of the stocks are disregarded because they have warrants listed on the SET. Four other stocks are omitted because they had rights issues during this period. Hence only thirty-four stocks consisting of 903,676 transactions records during the sample period from January 3, 1996 to June 13, 1996 remain to be divided into two equal portfolios based on high and low trading volume as shown in Table 2b. These stocks are noted to be mostly from the active trading deciles. Specifically, about half of the short list belongs in the first decile, about a quarter is in the second decile with the rest in the third to the fifth deciles. In other words, the seventeen members of the high SET-50 portfolio are a subset of the first decile, whereas half of the low SET-50 are from the second decile and the rest from the third to the fifth decile. Two-thirds of the stocks are traded daily, whereas one-third of the stocks are traded more than 85 percent of the time. The average stock trading volume is about 1,035,209 and 179,726 shares per day for the high and low SET-50, respectively. Furthermore, the high and low SET-50 portfolios have an average daily closing price of about 70 and 276 baht per share and an average market capitalisation of about 55 and 48.6 billion baht respectively[15].

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[14] The SET-50 Index is a market capitalisation weighted index calculated from share prices of 50 selected listed companies in the SET with large market capitalisation and high liquidity.

[15] The first (fifth) decile is characterised as having high (low) trading volume and large (small) capitalisation stocks; while both SET-50 portfolios can resemble the first decile, by construction the high SET-50 has a higher trading volume than the low SET-50. These four portfolios can be ranked by average trading volume as follows: high SET-50, first decile, low SET-50, fifth decile, with a large variation across the portfolios. By

Trading Days Selection: The trading process can be caused by both public and idiosyncratic news. By assumption, the current firm specific model considers each trading day as independent and each transaction as drawn from an identical independent distribution. To focus only on the firm-specific news, we eliminated the confounding effects of common or public news by using an arbitrary 1% filter for each daily SET index value. Consequently, out of the whole sample, there remained only 73 trading days in which the whole stock market fluctuated not more than ±1% from the previous day.[16] (The filter rule used on the index is new in solving the confounding effects, and deviates from EKOP.) A thirty trading day trading window during February and March 1996 was chosen to allow sufficient trade observations for our statistical estimation and inference to avoid the January effect, as per EKO.

Data Composition: Transaction data from the SET had to be adjusted to suit the requirements of the model in terms of aggregating buys, sells and no trades from observations of prices, volumes, time of trading and the definition as a buy or a sale. For this purpose, a trading interval has been defined to permit at most one event; however, differences between trading patterns across the deciles made it impossible to set an interval for which actively traded issues had single trades and the inactively traded issues were not virtually extinct. This problem is exacerbated by intraday "seasonality" as suggested by Hasbrouck [1995]. We found trading to

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average capitalisation, they rank: high SET-50, low SET-50, first decile, fifth decile, with all but the last well over 35 billion baht. Average stock prices are about 70 baht per share for all portfolios except the low SET-50.

16 Removal of this filter produced higher α and h_I for low volume stocks and lower δ and h_U for high volume stocks, with other parameters similar, compared to the results here .

be concentrated in some intervals, with both buy and sell transactions observed. Discreteness of the intervals is an important issue, as noted in EKO, who remarked that a one minute trading interval was appropriate for very active stocks but much too short for most stocks. They settled on a five minute interval for the much more actively traded NYSE sample as a period that could define a no trade event, then counted all buys and sells separately over any trading interval. In their paper on trade size, EKOP used a continuous process that referred to the arrival rates from informed and uninformed and ignores the counting of no trades.

In their theoretical results, EO found that the number of no trades did not affect the estimates for setting prices. We, in contrast, focus on the short-sale restriction and find the no trade information revealing. Hence, the proportion of no trades to trades of both kinds is significant. Neither the continuous modelling, with estimation of the arrival rates, nor the discrete, that counts trades as they occur but recognises no trades as periods of inactivity, would be suitable. In our judgment, counting individual trades separately and no trades as the number of intervals without trades would bias the estimates against recognising no trades as individual events. For that reason, we decided to follow the model specification of a common length trading interval during which buys, sells or no trades should occur; in this way, the relative intensity of buying, selling or no trading is estimated. Given the problem of estimation for the low volume portfolios with extremely low trading, we elected to use a ten minute interval as a standard, testing also five and fifteen minute intervals.

Since our prescribed interval length admits the occurrence of multiple trades, a method of aggregation was needed to characterise the trading result for such intervals. The method used is referred to as the "Net Trade Method" (NTM). If in a given interval more than one trade occurs, the net of buys over sells is considered as defining a buy if positive, a sell if negative and a no trade if zero. Using the NTM for the ten minute intervals, the average daily trade tuples (B,S,N) were (11,9,24) for the first decile, compared to (1,1,25) for the fifth decile and (8,6,4) for the high-SET portfolio and (11,6,8) for the low-SET portfolio.

The NTM aggregation is used since the model is based on numbers of trade occurrences as indicative of information or liquidity trading. An alternative aggregation of the total net buy or sell trading volume in a given interval is used to check for robustness. During the trading intervals as defined, one may find multiple buy and sell initiated trades of varying individual volumes. Netting the total volumes during the interval (e.g. 4,000 shares traded as buy initiatives and 1,000 shares traded as sell initiatives for a net buy volume of 3000 shares), if the result is positive, negative or zero then the interval defines an event as a buy, sell or no trade, respectively. This approach is described as the "Net Volume Method" (NVM). Neither method can escape the criticism that 101 buys versus 100 sells (or shares on each side) is a virtually neutral event; in terms of direction, it would imply neither a high or low signal, but it clearly does not imply a lack of trading. The realities of the trading pattern make the preferred alternative of single event intervals impossible, leaving us with a "second best" solution.

3.3 Tests of the Model and Parameters

Testing the applicability of the model to the data from the SET involves two issues, namely accuracy of the predictions about response to information affecting individual securities and the credibility of the parameters indicating the composition of the market. Since ex post convergence to equilibrium values per se is not empirically observable, we now will verify whether the alternative portfolios that we have defined exhibit distinct parameter values, from which we can estimate the convergence rates by equations (3) and (4). As a result, we will estimate the market parameters for different portfolios and determine whether the revealed differences are consistent or not with presumptions about market structure.

We have conjectured that higher volume, as in the first volume decile and the high SET-50 portfolio, tends to be associated more with good news than with bad news. By contrast, low volume, as in the fifth volume decile and the low SET-50 portfolio, suggests bad news or no news. Proposition 2 stated that when uninformed investors are equally likely to buy or sell (γ =1/2) and $h_I \neq h_U$, we would expect to find faster adjustment to bad news than to good news. Since it is conceivable that $\gamma \neq 1/2$, we must examine also this case where, in particular if $\gamma > 3/5$ (i.e. more sellers than buyers), the reaction to bad news may be slower than to good news. We shall calculate the estimates of convergence rates for the four different portfolios and compare them accordingly.

A variety of non-parametric tests including the Kolmogorov-Smirnov, Mann-Whitney and Chi Square tests, as discussed below, are used to examine the implications for differences in parameters, and their results are presented in the next sub-section. The statistical inferences, a derived p-value and the Bonferroni test are given in the following section.

We shall use a number of non-parametric or distribution-free approaches tests to determine whether the various portfolios are reasonably homogeneous in terms of the parameters and yet display significant differences with respect to some of those parameters between each other. The non-parametric tests to be performed are as follows:

One Sample Test: For stocks within a decile, a goodness of fit is tested by the *Kolmogorov-Smirnov* (KS) one-sample test; we assume an underlying Poisson distribution, since the trinomial distribution is asymptotically a Poisson distribution. This test verifies the correspondence of the distribution of sample values and the presumed Poisson distribution. The null hypothesis for each estimate of $\mathbf{Q} = \{\alpha, \delta, \mu, \gamma, h_I, h_U\}$ is:

$\mathbf{H_0: Q_i = Q_j}$ for i and j stocks in the same portfolio.

The null is then that there is no difference in the expected value of the estimated parameter for each stock across its own decile, and any observed differences are merely chance variations to be expected in a random sample from the theoretical Poisson population.

Two Independent Samples Test: To compare the medians between the two deciles, instead of a typical *t* (parametric) test of the means, the *Mann-Whitney* (MW) signed-ranks test or Wilcoxon test is used to provide a directional hypothesis. The alternative hypothesises are for each estimate of $\mathbf{Q} = \{\alpha, \delta, \mu, \gamma, h_I, h_U\}$:

$\mathbf{H_0}: \mathbf{Q}^{hi}_i = \mathbf{Q}^{lo}_j$

$\mathbf{H_1}: \mathbf{Q}^{hi}_i > \mathbf{Q}^{lo}_j$

for i and j stocks in the $\mathbf{Q}^{hi}$, first decile (high SET-50) portfolio

and the $\mathbf{Q}^{lo}$, fifth decile (low SET-50) portfolio, respectively.

Verification of the null hypothesis that the estimated parameter frequencies are stochastically equal for the paired sets would lead one to reject the theoretical results, since the high volume and low volume portfolios should not be the same, and the model has provided predictions on their relative sizes. Since the MW test is intended to determine if two independent groups have been drawn from the same population, the result is not conclusive; however, acceptance of the null would conflict with EKOP's finding concerning α and μ for volume deciles.

We also apply the χ^2 test in these cases to determine the significance of the differences between the pairings. The alternative hypothesis here is that the proportion of estimated parameters from stocks in the high and low volume sets is not drawn from the same population. The size of the χ^2 value reflects the magnitude of the discrepancy between the observed and the expected values. Note that the Kruskal-Wallis test used by EKOP is inappropriate here because of the discrete distribution underlying the current model. The hypotheses are as follows:

$\mathbf{H_0}$: $\mathbf{Q}^{hi}_{i} = \mathbf{Q}^{lo}_{j}$

$\mathbf{H_1}$: $\mathbf{Q}^{hi}_{i} \neq \mathbf{Q}^{lo}_{j}$

for i and j stocks in the $\mathbf{Q}^{hi}$, first decile (high SET-50) portfolio

and the $\mathbf{Q}^{lo}$, fifth decile (low SET-50) portfolio, respectively.

4. Results of Parameter Estimation and Testing

4.1 The Parameter Estimation Results Discrete time trading model parameter estimates with standard errors in parenthesis are presented for each stock in Table 4a,b, the first and fifth decile in Table 4a, Panels A and B, and the high and low SET-50 portfolios in Table 4b, Panels A and B. For illustration, KTB (Krung Thai Bank PLC) appears in 4aA (third from bottom) and 4bA (first decile and high SET-50 portfolio) and shows a market capitalization of 179.7 billion baht. For KTB there is estimated an α = 0.6659 probability of an information event occurrence on any given day, for which there is a δ = 0.5711 probability of a low signal. In a given trading interval, there is a μ = 0.3212 probability that a trade comes from an informed trader having an h_I = 0.5343 chance of owning the stock. 66.88% of trades are expected to come from uninformed traders with probability of h_U = 0.6809 of already owning the stock and a γ = 0.6388 chance of wanting to sell. Overall results show that the mean of the estimated parameters for each stock differs widely within its own decile and between deciles.

Table 5 aggregates Tables 4a and 4b, displaying the means, medians and standard deviations of the estimated parameters for the first and the fifth deciles, and for high and low volume SET-50 portfolios. On average, the high volume stocks appear to have higher estimates of α, h_I and h_U, but lower estimates of δ, μ and γ than the low volume stocks. It seems that the estimated parameters are greatly varying, as evidenced by a wide range of standard deviations. Table 6 presents non-parametric test results with Panel A showing the KS one sample test and Panel B the two sample χ^2 and MW tests. Except for γ and h_I in the volume decile case, the KS test results cannot reject at the 95% confidence level the null hypotheses, implying most stocks within groups come from the same population. By contrast, all χ^2 statistical results reject equality of parameters at the 95% confidence level, implying the paired groups are composed of distinct populations. For the Mann-Whitney test results, the high volume stocks seem to have higher estimates of α, μ and h_I, and lower estimates of δ, γ and h_U than the low volume stocks.

4.2 Analysis of the Parameter Estimates

Probability of an Information Event (a) - This is also referred to as the (firm specific) information intensity of the stock. The model predicts that active (inactive) stocks should have high (low) information intensity. Thus if the probability of an information event's occurrence before the beginning of the trading day is high (low), then trading activities should be high (low). The KS test reveals that for both volume decile and SET-50 cases, one cannot reject that the estimated α are drawn from the same population. Hence, grouping stocks according to trading volume is appropriately done and the average result may represent the whole group sample. The high χ^2 values of 46.6015 and 28.17728 indicate a large difference between the two sample populations in both the decile volumes and SET-50 portfolios, respectively. The MW test confirms that the first decile's α frequencies are stochastically larger than the fifth decile's α with a score of 3.5460 (significant at the 95% level). For the SET-50 portfolios the α value is also higher for the high volume portfolio, but not significant. It is apparent that active stocks have stochastically and significantly higher information intensity than inactive stocks, as predicted by the model.

Probability of Bad News (d) - The implication of the model is that low (high) volume stocks should have a high (low) probability of bad news, δ, or that active (inactive) stocks are associated with good (bad) news under a short sale restriction. Again the KS test rejects at the 95% level for both pairs of groups that the parameters are not consistent within groups; hence, the volume grouping is appropriately done. High χ^2 values of 57.6298 and 31.82591 indicate large variations between the two sample populations in both the volume deciles and SET-50. The MW test finds significant (2.6416) difference in means for the volume deciles and less significant (1.2917) difference for the SET-50 portfolios. In both cases, however, the means and medians are lower for the high than for the low volume groups, thus providing support for the conjecture that low (high) volume stocks are associated with bad (good) news, as stated by Proposition 2.

Probability that a Given Trader Is Informed (μ): No prediction is made by the model for this parameter. One might expect higher activity in stock trading to reflect the presence of information or alternatively, to find insider trading to be more prevalent in less well known and less traded stocks. EKOP found that informed traders are less likely to participate in high volume stocks than in low volume stocks. Inspection of the basic statistics in Table 5 indicates a higher estimate of informed traders for the first decile than the fifth decile, as measured by the means but not by the medians; for the high and low SET-50 portfolios, means and medians were approximately equal. On the other hand, variances for the high volume groups were noticeably lower than for low volume. The KS tests do not reject the homogeneity of the groupings, while χ^2 values of 39.0688 and 33.2171 for the decile and SET-50 comparisons indicate strong differences. The MW results, however, show a difference of -.2629 for the deciles and +.4995 for the SET-50 portfolios, neither of which is significant.

Probability of an Uninformed Trader Selling (γ): The basic hypothesis, accepted by EKO, is that the γ value is 0.5 to ensure a zero net supply from uninformed traders in the market. The classification as an informed trader is not stable over time, however; one could conjecture that informed traders hold the stock in order to profit from their information, but that if they recognise there is no information advantage they would sell their stock as they become uninformed, preferring to invest only in superior knowledge situations. Thus the uninformed investor, when joined by a previously informed investor, might be biased to sell, giving $\gamma > 0.5$. The KS test reveals γ estimates to be drawn from different populations in the first and the fifth deciles, but not in the SET-50 groups; that is, the decile groupings are *not* homogeneous for γ. The χ^2 tests indicate that the parameters of the two deciles and the SET-50 portfolios are drawn from different populations, with significant values of 6.2301 and 8.1254. MW test scores of -6.7649 and -3.9093 are highly significant, indicating that the probability of an uninformed trader being a seller is lower when trading in the more active stocks. The level of the estimates is surprisingly high, ranging from .6036 to .8763, considering the usual assumption. It has been pointed out, however, that if one compares the estimated probabilities of uninformed buys (1-γ) and sells (γ h_U), the values are quite similar (e.g. .3524 and .3268 respectively for the first decile); that is, the actual probabilities of these trades are symmetric.

Probability of an Informed Trader Owning the Stock (h_I): Although the model does not predict any particular level or pattern for this parameter, its results do require a relationship between it and h_U and γ, given by (2). The KS test results show that the estimated h_I are drawn from different populations in the decile groups, with significant levels, but from the same population in the SET-50 grouping; this suggests that grouping by turnover does not provide homogeneity of insider ownership, but high capitalisation SET-50 stocks are more likely to have consistent insider ownership. The χ^2 test results show significant differences between the pairings for both deciles and SET-50 groups, with values of 42.1212 and 28.6379. The MW test shows that both the lower volume decile and SET-50 portfolios have higher proportions of ownership by insiders, but the numbers are not significant. The standard deviation is high in all groups, and there is a tendency towards extreme values in the results (i.e., close to 1 or to 0).

Probability of an Uninformed Trader Owning the Stock (h_U): Liquidity traders are likely to prefer active stocks to inactive stocks for ease of liquidation and also if they suspect that inactive stocks are vulnerable to informed trading. Other than the relationship mentioned above, the model makes no predictions about h_U. Unlike the previous case, the KS test here admits the homogeneity of the various groups for the parameter, while again the differences in the estimated parameters between the pairings is significant with χ^2 values of 9.5615 and 20.5971 for decile and SET-50 pairs. MW test results show the significantly larger proportion of holdings by uninformed traders of both higher volume groups; mean ownership ranges from .5740 to .1285, with difference larger for the decile pairs than for the SET-50, and the dispersion among individual stocks within groups is quite low, especially compared to the informed investor results.

4.3 Inferences and Discussion

Bonferroni Test

We also tested the resulting parameter estimates for support of the general model. This consisted of using the estimated parameters to calculate the probability of observing a particular trade-tuple on a particular day, and comparing that with the value predicted by the model. We can then analyse the individual stocks from their trading patterns observed over the time period, and ultimately make a simultaneous confidence statement, using Bonferroni inequality tests. Specifically, MLE provides estimates of **Q** which are used to compute the probability of the trades (i.e., Pr{B}, Pr{S}, Pr{N} and Pr{B,S,N}) for particular stocks and days. For indefinitely repeated trials, the theoretical probability of observing these trade-tuples in any given day, for a trinomial distribution, tends to:

$$\Pr\{B,S,N\} = t!\,/\,[B!\,S!\,(t-B-S)!]\quad \Pr\{B\}^{B}\ \Pr\{S\}^{S}\ \Pr\{N\}^{t-B-S} \qquad (11)$$

$$\text{where}\quad t = B + S + N \quad\text{and}\quad \Pr\{Q\} = \sum_{\Psi\in\{H,L,0\}} \Pr\{Q \mid \Psi\} \quad\text{for}\quad Q \in \{B,S,N\}$$

The inferred Pr{B,S,N} is the parameter (p)-value corresponding to the observed event with the highest probability. We use a significance level of 1% to reject or accept the parametric model of formula (8). Table 7 shows a sample case using KTB trading.

Because the current analysis is restricted to a number of individual probabilistic statements for particular stocks in a given test period, the Bonferroni method of multiple comparisons is applied. The Bonferroni inequality states that the joint probability of all *true* confidence statements must be equal or greater than one less the sum of the joint probability of all *false* confidence statements. Suppose C_i is a confidence statement about the specified joint mean value of $E[f(B_i,S_i)] = 1 - p_i$ for i = 1,2,...,d. Then

$$\Pr\{\text{all } C_i \text{ true}\} = 1 - \Pr\{\text{at least one } C_i \text{ false}\}$$

$$\geq 1 - \Sigma_\iota \Pr\{C_i \text{ false}\} = 1 - \Sigma_\iota [1 - \Pr\{C_i \text{ true}\}]$$

$$= 1 - (p_1 + p_2 + \ldots + p_d)\,/\,d \qquad (12)$$

In the KTB case, for example, the total sum of the *p*-values is 0.9873 as shown in Table 7. This implies the overall error rate $(p_1 + p_2 + ... + p_d)/d = 0.0127$ for which all confidence statements are correct can be controlled, regardless of the correlation structure behind the confidence statements. Also, providing a large sample size enables the elimination of serious departures from a normal population.[17] Tables 8 a and b present the

p-values as well as the unconditional theoretical probabilities of buys, sells and no trades for individual stocks in the first and fifth deciles, and the high and low SET-50 portfolios. Table 8a and 8b reveal that almost all of these stocks have *p*-values above .01 seventy percent of the time, and none of the cases breaks the Bonferroni bounds at the 95% confidence level. These results signify that the model cannot be rejected.

Robustness Check

The first alternative that we proposed was to vary the trading interval length from the ten minutes presented to five and fifteen minutes. On the whole, the estimates are reasonably stable across the interval changes, although estimates of h_U are particularly sensitive being greatly increased as the interval length increases. μ also is sensitive with significant decreases in its estimate as the interval increases in most of the partitions. Although there are visible changes in the estimates, it is perhaps surprising how many of them are relatively insensitive to the interval length.

We also considered the method of aggregation of the trades to determine the net effect for the interval, using the NVM (volume) instead of counting trades, or NTM. Tables 9a and b

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[17] See Johnson and Wichern [1988, pp. 188-192].

present the estimates of parameters by NTM and NVM, respectively, for each of the trading interval lengths. The two information parameters α and δ appear to be relatively consistent. Comparing 9a with 9b figures, there is little change in each of the estimates, and furthermore, there are relatively small changes within each table for the different interval lengths. The greatest change appears to be in the estimates of δ for the low SET-50 portfolio, with the NVM giving more variation than the NTM; the high SET-50 portfolio δ also varies for the NVM but not for the NTM. The estimate of the proportion of informed investors μ also seems to be quite invariant to the interval, with a slight bias to higher estimates by NTM.

The probability of selling by uninformed investors γ seems to be relatively stable across the two variations, but there appears to be a consistent, if slight, direction to the changes. A shorter interval is consistently associated with a higher estimate for the parameter; similarly, the NTM consistently gives higher estimates than the NVM, so that an NTM estimate based on five minutes is largest. Estimates of the ownership parameters h_I and h_U, on the other hand, appear to rise as the trading interval increases; this is consistently true for the uninformed investors, but reversals occur for the low SET-50 portfolio and for all except the first decile by NTM.

Predictions of the Model

One important relationship to examine is the condition (2) on the propensity to sell short. This relationship is *not* supported conclusively, although some patterns emerge. The NVM gives slightly better results than the NTM, but there is a consistency in cases that generally agree or not with the condition; the longer trading interval leads to more confirmation. The first decile and high SET-50 portfolio confirm the result except for a slight reversal by NTM at five minutes for both groups. The fifth decile rejects the condition universally, and by a large inequality, as the left hand side, with estimates of very high γ combined with very low h_U, is far greater than the complement of the high h_U. The low SET-50 similarly rejects at the five minute interval and improves to a small confirmation as the interval increases.

Proposition 3 characterised the rate of convergence when a low signal has been generated. For equal ownership proportions, the rate is minimised, and for combinations of low h_U with high h_I, or the opposite, the rate is maximised. The base case estimation method showed the ownership proportions to be approximately equal and close to one half for the high volume groups, while h_U was fairly low for the low SET-50 portfolio and very low for the fifth decile. For these latter two groups, as mentioned above, h_I was too high to satisfy condition (2), suggesting a high convergence rate.

Proposition 2 predicts that the speed of price adjustment on bad news is *faster* than on good news when γ =1/2; but if γ is sufficiently large (i.e. above a certain minimum based on μ, as in Figure 4a), then the reverse is true. That is, if the probability of an uninformed trader wanting to sell is sufficiently large, then the speed of price adjustment on bad news is *slower*. In this case, the market maker obtains less information from the trading process as the uninformed trader increases his participation (i.e. more noise), particularly in the sell cases. To test this, we substituted the mean estimates for 5, 10 and 15 minute trading intervals in Table 9a into equation (1), which defined the entropy expression for the rate of convergence.

The results are summarised in Table 10a. The minimum NTM estimate of γ was .57838, and generally above the minimum value necessary to reverse the result of Proposition 2;

hence, the rate of convergence is predicted to be greater on good news. As shown, this prediction is uniformly confirmed for all trade intervals. There is a general pattern of increasing speed with shorter trading intervals, which is always maintained for the good news cases. Combining the relationships expressed for the parameters as noted in the above paragraphs, the conditions existing for the fifth decile point to relatively higher convergence rates than for other deciles, which also appears to be true. Although the expected conclusion of faster convergence turns out to be false, the predicted behaviour appears to follow the theoretical predictions under the prevailing market conditions.

Theorem 2 predicts that the imposition of a short sale prohibition, in general, improves the informational efficiency of the market by increasing the speed of stock price convergence to its equilibrium value in bad news cases and leaving it unaffected in good news cases. This conclusion is tested by setting the ownership parameters to the value one, thereby permitting sales as desired, and using the remaining parameters in equation (1) for the convergence rates[18]. The results are illustrated by a comparison of Tables 10 a and b. In all cases, the convergence rate in the bad news case is much slower, but the convergence rate in the good news situation is unaffected since informed investors will not wish to sell.

5. Conclusion

This paper has presented a discrete framework for analysing the arrival of trades and no trade events in reaction to the revelation of information to a select group of investors when short

[18] Forcing $h_I = h_U = 1$ in a new regression would not be compatible with data generated from a market with short sales permitted.

sales are prohibited. Earlier work predicted volume to be correlated with return due to the type of news and examined the adjustment process in time. The rate of convergence was defined by applying the theory of probabilistic information measures or relative entropy; it was shown to be higher on the receipt of low signals compared to higher signals, but this result depended on the relative values of market parameters. Various conditions were noted to be necessary for the development of the theory; the most universal of these was stated as there being a higher propensity to short sell by informed investors, based on the ownership proportions of the stock. It was also possible to characterise the convergence rate for bad news signals, which form the basis for the analysis of short selling behaviour. The market maker is presumed to learn more rapidly about bad news due to the short sale constraint, using the observation of a low volume of trade to increase his estimate of the probability of a low signal and his speed of downward price adjustment. The short sale constraint is clearly found to affect the adjustment speed in price formation.

We interpreted the condition of $h_I = h_U = 1$, where these are the proportions of ownership of a stock, as being equivalent to permission of short sales by both informed and uninformed traders, since they would be free to sell for any reason. When $0 < h_I < 1$ and $0 < h_U < 1$, the market prohibits both types of investors from short selling; at the same time, both types are present in the market. If either type may not short sell or is not present, then the situation becomes degenerate and news is either fully revealed by insider behaviour or is not present. The model concludes that the short sale prohibition on all agents actually *improves* informational efficiency, especially with respect to private bad news, in contrast to Diamond and Verrecchia's

[1987] claim that the short-restriction imposed only on uninformed traders *reduces* market efficiency. Diamond and Verrecchia similarly find a no trade event to be somewhat informative as bad news, as opposed to Easley and O'Hara's [1992a] interpretation of it as no news. An immediate extension would be to determine if the structure can be relaxed to examine the restriction of short sales at a given cost, as investigated by Diamond and Verrecchia.

Our results were tested empirically by a maximum likelihood estimation of the parameters of market structure and information generation. The tests were performed on a sample drawn from trading on the Stock Exchange of Thailand, where an absolute prohibition of short-selling exists and where insider trading is thought to be common. The results gave new support to the previous contention that the volume of trading, measured by turnover, can be used to infer the existence of only partly released information. Estimating the parameters for different volume-based groups led to significantly different values for most of the parameters, in patterns that were generally compatible with the predictions of the model. Although the expected result on the speed of convergence was not supported by the data, this was due to parameter values which were predicted to yield the contrary result. In this way, the model appears to be substantiated, and certainly it is not rejected by the testing.

References

Admati, A. and P. Pfleiderer [1988] ‘A Theory of Intraday Patterns: Volume and Price Variability,’ Review of Financial Studies 1, 3-40.

Amihud, Yakov and Haim Mendelson [1986] ‘Asset Pricing and the Bid-ask Spread,’ Journal of Finance 42, 533-53.

Bollerslev, T. [1986] ‘Generalized Autoregressive Conditional Heteroscedasticity,’ Journal of Econometrics 31, 307-327.

Brennan, M. J. and A. Subrahmanyam [1995] 'Market Microstructure and Asset Pricing: On the Compensation for Market Illiquidity in Stock Market,' working paper 190, London Business School (LBS).

Brown, D. P., and R. H. Jennings [1989] , "On Technical Analysis", Review of Financial Studies, 2, 4, 527-551.

Cover, Thomas M. and Joy A. Thomas [1991] Element of Information Theory , New York: John Wiley & Sons, Inc.

Diamond, D. W., and R.E. Verrecchia [1989], " Constraints on Short Selling and Asset Price Adjustment to Private Information", Journal of Financial Economics, 18, 277-311.

Diamond, Douglas W. and Robert E. Verrecchia [1987] ‘Constraints on Short-Selling and Asset Price Adjustment to Private Information,’ Journal of Financial Economics 18, 277-311.

Easley, David and Maureen O'Hara [1987] 'Price, Trade Size and Information In Securities Market,' Journal of Financial Economics 19, 69-90.

Easley, D., and M. O'Hara [1992a], "Time and the Process of Security Price Adjustment", Journal of Finance, 47, 577-606.

Easley, D., and M. O'Hara [1992b] 'Adverse Selection and Large Trade Volume: The Implications for Market Efficiency,' Journal of Financial and Quantitative Analysis 27, 185-208.

Easley, David, Nicholas M. Kiefer and Maureen O'Hara [1995] 'One Day in The Life of a Very Common Stock,' working paper, Cornell University.

Easley, D., N. Keifer, M. O'Hara and J. Paperman [1996] 'Liquidity, Information, and Infrequently Traded Stocks', Journal of Finance, 51.

Figlewski, Stephen [1981] 'The Information Effects of Restrictions of Short Sales: Some Empirical Evidence,' Journal of Financial and Quantitative Analysis16, 463-476.

Fletcher, Roy A. [1995] 'The Role of Information and The Time Between Trades: An Empirical Investigation', Journal of Financial Research 18, 239-260.

Foster, F. D. and S. Viswanathan [1990] 'A Theory of the Intraday Variations in Volume, Variance and Trading Costs in Securities Market,' Review of Financial Studies 3, 593-624.

Gallant, A., Peter E. R., and G. Tauchen [1992] 'Stock Prices and Volume', Review of Financial Studies 5, 199-242.

Glosten, Lawrence R. and Paul R. Milgrom [1985] 'Bid, Ask and Transaction Prices in a Specialist Market with Heterogenously Informed Traders,' Journal of Financial Economics 13, 71-100.

Grossman, S. J. [1976] "On the Efficiency of Competitive Stock Markets Where Traders Have Diverse Information", Journal of Finance, 31, 573-585.

Grossman, S. J. [1978], "Further Results on the Informational Efficiency of Competitive Stock Markets", Journal of Economic Theory, 18, 81-101.

Grossman S. J., and J. Stiglitz [1980] "On the Impossibility of Informationally Efficient Markets", American Economic Review, 70, 393-408.

Grundy, B. D., and M. McNichols [1989], "Trade and the Revelation of Information through Prices and Direct Disclosure Markets", Review of Financial Studies, 2, 4, 495-526.

Harris, Lawrence [1991] 'Stock Price Clustering and Discreteness', the Review of Financial Studies, pp. 389-415.

Harris, Lawrence [1994] 'Minimum Price Variations, Discrete Bid-Ask Spreads, and Quotation Sizes,' Review of Financial Studies, 7, 149-178.

Harris, M. and A. Raviv [1993] 'Differences of Opinion Make a Horse Race,' Review of Financial Studies 6(3), 473-506.

Hausman, J., A. W. Lo and A. C. MacKinlay [1992] 'An Ordered Probit Analysis of Transaction Stock Prices,' Journal of Financial Economics 31, 319-79.

Hasbrouck, Joel [1995] ‘Modeling Market Microstructure Time Series,’ discussion paper, the Stern School of Business, New York University.

He, H. and J. Wang [1995] ‘Differential Information and Dynamic Behavior of Stock Trading Volume,’ Review of Financial Studies 8(4), 917-972.

Hoontrakul, Pongsak [1995a] 'Turnover Anomaly: Thailand Case', working paper, Joint Doctoral in Business Administration Program (JDBA), Chulalongkorn University, Thammasat University and National Institute of Development Administration, Bangkok, Thailand

Hoontrakul, Pongsak [1995b] 'Market Microstructure Comparison: USA, Japan and Thailand,' Chula Review 26, Chulalongkorn University, Bangkok, Thailand, 78-88.

Hoontrakul, Pongsak, Peter Ryan, Anya Khanthavit and Stylianos Perrakis [1999] 'Market Microstructure in an Emerging Market with Short Sales Constraints: Theory and Empirical Evidence from the Stock Exchange of Thailand’ working paper.

Holthausen, Robert W. [1990] ‘Large-Block Transactions, the Speed of Response, and Temporary and Permanent Stock-Price Effects,’ the Journal of Financial Economics 26, 71-95.

Jones, Charles M., Gautam Kaul and Marc L. Lipson [1994] ‘Transactions, Volume, and Volatility,’ the Review of Financial Studies 7, 631-651.

Johnson, R.A. and Wichern, D.W. [1988] ‘Applied Multivariate Statistical Analysis,’ 2nd Edition, Prentice - Hall Inc., 1988, 607pp.

Karpoff, J. [1987] ‘The Relationship between Price Changes and Trading Volume: A Survey,’ Journal of Financial and Quantitative Analysis 22, 109-126.

Kim, O., and R. E. Verrecchia [1991a], "Trading Volume and Price Reactions to Public Announcements", Journal of Accounting Research, 29,2, 302-321.

Kim, O., and R. E. Verrecchia [1991b], "Market Reaction to Anticipated Announcements", Journal of Financial Economics, 30, 273-309.

Kyle, A. S. [1985] 'Continuous Auctions and Insider Trading,' Econometrica 53, 1315-1336.

Kyle, A. S. [1989], "Informed Speculation with Imperfect Competition", Review of Economic Studies, 56, 317-356.

Milgrom, Paul R. and Nancy Stockey [1982] ‘Information, Trade and Common Knowledge,’ Journal of Economic Theory 26, 17-27.

O’Hara, Maureen [1995] Market Microstructure Theory, Boston, Mass: Blackwell Publishers.

Seppi, D. J. [1990] ‘Equilibrium Block Trading and Asymmetric Information’, the Journal of Finance 5, 281-306.

Seppi, D. J., [1996] ‘Liquidity Provision with Limit Orders and a Strategic Specialist,’ Review of Financial Studies.

Stickel, S.E. and R. E. Verrecchia [1993] ‘Evidence that Volume Sustains Prices Changes,’ working paper, the Wharton School.

Vives, X. [1995] "Short-Term Investment and the Informational Efficiency of the Market", Review of Financial Studies, 8, 1, 125-160.

TABLE 1: A summary of notation used throughout the paper

Notation	Definition
V	The value of the risky asset per share. $V_H \equiv E\{V \mid \boldsymbol{Y}=H\}$; $V_L \equiv E\{V \mid \boldsymbol{Y}=L\}$; $V^* \equiv E\{V \mid \boldsymbol{Y}=0\}$ where $V_H > V^* > V_L$.
$\boldsymbol{Y}$	a signal that V is either high (H), low (L) or no signal (0). $\boldsymbol{Y} \in [0,H,L]$
α	The probability that an information event occurs. $0<\alpha<1$.
δ	The probability that a low signal $\boldsymbol{Y}=L$ occurs. $0<\delta<1$.
γ	The probability that an uninformed trader wants to sell. $0<\gamma<1$.
μ	The probability that a given trader is informed; also the fraction of informed traders in the market. $0<\mu<1$.
h_I	The probability that a given informed trader already owns the stock. $0<h_I<1$.
h_U	The probability that a given uninformed trader already owns the stock. $0<h_U<1$.
B	The event that a trader buys a single unit quantity.
S	The event that a trader sells a single unit quantity.
N	The event that no trade occurs.
τ	A trade event occurs as either buy or sell. $\tau = \{B,S\}$.
n_t	The total of no trade events up to time t.
β_t	The total buying volume of the traded asset up to time t.
s_t	The total selling volume of the traded asset up to time t.
v_t	The total trading volume of the traded asset up to time t. $v_t = \boldsymbol{b}_t + s_t$.
Q_t	The event of a buy, a sell or no trade at time t. $Q_t \in [B_t, S_t, N_t]$.
Q^{t-1}	The sequence (vector) of past trading outcomes. $Q^{t-1} = [Q_1, Q_2, ..., Q_{t-1}]$.
$\rho_{\psi,t}$	The conditional probability of signal $\psi \in [H,L,0]$, given trade history $Q^{t-1} = [Q_1, Q_2, ..., Q_{t-1}]$. (i.e. $\rho_{\psi,t} \equiv Pr.\{\psi \mid Q^{t-1}\}$)
$\rho^{Q}_{\psi,t+1}$	The conditional probability of signal $\psi \in [H,L,0]$, given one more trade, $Q_t \in [B_t, S_t, N_t]$ with the observation of trade history, $Q^{t-1} \equiv [Q_1, Q_2, ..., Q_{t-1}]$.
θ_ψ	The conditional probability of a no trade event given signal ψ.
$I_{P^\psi}(P^{\psi'})$	The relative entropy under probability law $P^{\Psi'}$ given that $P^{\Psi} = Pr.\{Q \mid \Psi\}$ is true.

Table 2a : Selective Stocks for First (Most Active) and Fifth (Average Active) in Sample During Jan 3, 1996 To June 13, 1996.

Panel A : First (Most Active) trading volume deciles stocks.

Ticker	**Public Company Limited Name**	**Average Closing Price *1**	**Daily Trading Volume (10^{6})**	**Market Capitalization (10^{6}) *2**
BBC*	Bangkok Bank of Commerce	19.09	2.4231686	24,900.69
BBL	Bangkok Bank	240.53	0.84769118	240,836.68
BCHANG	Ban Chang Group	9.53	0.86849222	2,716.05
BCP	The Bangchak Petroleum	34.36	0.49312843	17,937.29
BECL	Bangkok Expressway	43.28	1.3582505	33,325.60
BOA	Bank of Asia	55.02	0.40474706	23,110.79
CAPE	Capetronics Int'l (Thailand)	4.08	0.39117353	1,029.18
CMIC	Cmic Finance & Securities	87.11	1.12649216	16,798.37
CPICO	Central Paper Industry	47.77	0.56598889	2,866.20
DEFT	Dynamic Eastern Finance Thai	48.56	0.36330294	8,643.68
EGCOMP	Electricity Generating	86.82	1.07983922	45,146.40
FBCB	First Bangkok City Bank	28.09	1.67394118	28,090.00
FCI	First City Investment	37.84	0.51395588	10,027.60
ITF	International Trust & Finance	20.67	0.52152255	5,031.82
KTB	Krung Thai Bank	121.46	1.16612745	179,700.07
KTT	Krung Thai Thanakit	120.05	0.71771275	27,157.71
NAVA	Nava Finance & Securities	77.95	1.42088824	17,538.75
NPC	National Petrochemical	42.71	0.85853333	13,240.10
ONE	ONE Holding	69.22	0.68418485	11,075.20
PHATRA	Phatra Thanakit	192.32	0.35130882	53,317.64
RR	Rattana Real Estate	19.15	0.48738812	1,551.15
SATTEL	Shinawatra Satellite	41.53	0.53811863	14,535.50
SCB	Siam Commercial Bank	293.97	0.29980098	111,944.66
SCCF	Siam City Credit Finance & Securities	111.6	0.38362941	5,803.20
SITCA	Sitca Investment & Securities	46.13	0.32305686	9,917.95
SOMPR*	Somprasong Land	40.75	0.44718427	1,459.34
SSI	Sahaviriya Steel Industries	26.23	1.11751078	13,377.30
SUSCO	Siam United Services	6.96	0.63190588	1,231.92
TA	Telecom Asia Corporation	69.77	1.59479804	155,098.71
THAI	Thai Airways International	50.71	0.39508119	70,994.00
TMB	The Thai Military Bank	102.28	1.41818333	52,490.87
TMP	Thai Melon Polyester	13.16	0.71278713	2,026.64
TYONG	Tanayong	39.92	0.35613267	12,233.72
WAT	Wattachak	49.53	0.36288617	9,231.65
	Mean.	67.5926	0.7911	36,011.3659

*1 Average price is calculated as the arithmatic mean of daily closing price during Jan 3,1996 To June 13,1996

*2 Market capitalization is calculated as the product of average daily closing price during the sample period and total register shares in the last trading period.

* Suspend in trading after May 28, 1996

Table 2a : **Selective Stocks for First (Most Active) and Fifth (Average Active) in Sample During Jan 3, 1996 To June 13, 1996.**

Panel B : Fifth (Average Active) trading volume deciles stocks.

Ticker	Public Company Limited Name	Average Closing Price *1	Daily Trading Volume (10^6)	Market Capitalization (10^6) *2
AFC	Asia Fiber	12.13	0.02824946	451.236
AITCO	Ayudhya Investment & Trust	167.13	0.02746629	5,013.90
AMARIN	Amarin Plaza	21.99	0.02491368	2,226.49
APRINT	Amarin Printing Group	26.86	0.03178353	510.34
BKP	Bangkok Produce Merchandising	21.22	0.02267941	1,273.20
CATHAY	Cathay Finance & Securities	44.27	0.018496	2,213.50
CENTEL	Central Plaza Hotel	8.98	0.02037391	1,616.40
CPF	Charoen Pokphand Feedmill	123.02	0.02643824	14,762.40
CTW	Charoong Thai Wire & Cable	56.41	0.02010842	1,692.30
EWC	Eastern Wire	47.72	0.03019208	855.94
HEMRAJ	Hemaraj Land & Development	155.88	0.02833069	11,030.94
JUTHA	Jutha Maritime	22.43	0.02249121	481.12
LOXLEY	Loxley	415.36	0.02698586	16,614.40
N-PARK	Natural Park	52.66	0.02160594	19,905.66
NC	New City (Bangkok)	34.6	0.02955269	415.20
ONPA	ONPA International	155.64	0.02116863	7,782.00
PATKOL	Patkol Co	21.23	0.02257849	225.04
PE	Premier Enterprise	39.73	0.02319691	3,178.40
PP	Power-P	76.42	0.0272049	1,910.50
PRANDA	Pranda Jewelry	45.29	0.02386875	679.35
PRG	Patum Rice Mill & Granary	22.07	0.03064607	1,324.20
S & P	S & P	18.17	0.03224625	545.10
SAFE	Safety Insurance	26.98	0.02156702	958.54
SAWANG	Sawang Export	25.32	0.02062211	607.68
SSC	Serm Suk	507.98	0.02629222	13,207.48
STANLY	Thai Stanley Electric	105.17	0.03082947	4,029.27
SVH	Samitivej	20.78	0.02860435	1,246.80
SVOA	Sahaviriya OA	46.21	0.02898824	1,386.30
THORES	Thoresen Thai Agencies	69.3	0.02222041	2,079.00
TPC	Thai Plastic & Chemicals	131.63	0.0183866	11,517.63
TRU	Thai Rung Union Car	96.19	0.02167129	3,847.60
TVI	Pacific Insurance	44.49	0.02018901	449.35
UFC	Universal Food	7.64	0.0319913	267.40
VIBHA	Vibhavadi Medical Center	13.15	0.02001556	472.93
	Mean.	78.9426	0.0251	3,964.0470

*1 Average price is calculated as the arithmatic mean of daily closing price during Jan 3,1996 To June 13,1996

*2 Market capitalization is calculated as the product of average daily closing price during the sample period and total register shares in the last trading period.

* Suspend in trading after May 28, 1996

Table 2b : Selective Stocks for High and Low in Sample During Jan 3, 1996 To June 13, 1996.

Panel A : High Trading Volume SET-50.

Ticker	Public Company Limited Name	Average Closing Price *1	Daily Trading Volume (10^6)	Market Capitalization (10^6) *2
BBC*	Bangkok Bank of Commerce	19.09	2.4231686	24,900.69
BBL	Bangkok Bank	240.53	0.84769118	240,836.68
BCP	The Bangchak Petroleum	34.36	0.49312843	17,937.29
BOA	Bank of Asia	55.02	0.40474706	23,110.79
CMIC	Cmic Finance & Securities	87.11	1.12649216	16,798.37
EGCOMP	Electricity Generating	86.82	1.07983922	45,146.40
FBCB	First Bangkok City Bank	28.09	1.67394118	28,090.00
KTB	Krung Thai Bank	121.46	1.16612745	179,700.07
NAVA	Nava Finance & Securities	77.95	1.42088824	17,538.75
NPC	National Petrochemical	42.71	0.85853333	13,240.10
ONE	ONE Holding	69.22	0.68418485	11,075.20
SATTEL	Shinawatra Satellite	41.53	0.53811863	14,535.50
SSI	Sahaviriya Steel Industries	26.23	1.11751078	13,377.30
TA	Telecom Asia Corporation	69.77	1.59479804	155,098.71
THAI	Thai Airways International	50.71	0.39508119	70,994.00
TMB	The Thai Military Bank	102.28	1.41818333	52,490.87
TYONG	Tanayong	39.92	0.35613267	12,233.72
	Mean.	70.1647	1.03521	55,123.7912

Panel B : Low Trading Volume SET-50.

Ticker	Public Company Limited Name	Average Closing Price *1	Daily Trading Volume (10^6)	Market Capitalization (10^6) *2
AA	Advance Agro	66.14	0.06027912	23,479.70
ACL	Asia Credit	174.41	0.09288627	13,342.96
ADVANC	Advanced Info Service	466.15	0.19003824	109,079.10
AST	Asia Securities Trading	76.18	0.28836765	9,903.40
B-LAND	Bangkok Land	31.44	0.19270297	18,864.00
JASMIN	Jasmine International	107.32	0.22958529	35,801.95
LOXLEY	Loxley	415.36	0.02698586	16,614.40
MDX	M.D.X.	42.01	0.28536139	6,958.13
NTS	N.T.S. Steel Group	24.21	0.24107451	5,120.42
PHATRA	Phatra Thanakit	192.32	0.35130882	53,317.64
PTTEP	PTT Exploration & Production	314.72	0.16875686	97,563.20
SCB	Siam Commercial Bank	293.97	0.29980098	111,944.66
SCC	The Siam Cement	1239.69	0.03735149	148,762.80
SCCC	Siam City Cement	362.15	0.08267059	42,386.03
SHIN	Shinawatra Computer&Communication	641.81	0.07465686	88,954.87
TPIPL	TPI Polene	141.49	0.24468333	35,903.09
UAF	Union Asia Finance	109.51	0.18883366	8,895.75
	Mean.	276.4047	0.17973	48,640.7116

*1 Average price is calculated as the arithmatic mean of daily closing price during Jan 3,1996 To June 13,1996

*2 Market capitalization is calculated as the product of average daily closing price during the sample period and total register shares in the last trading period.

* Suspend in trading after May 28, 1996

Table 3 : After +/- 1% filter rule on SET index, the selected date for investigation are listed as follows.

1996	SET INDEX	Δ SET	≤ 1%	DATE	SET INDEX	Δ SET	≤ 1%	DATE	SET INDEX	Δ SET	≤ 1%
19960103	1323.43		NO	19960222	1361.42	-0.01302	NO	19960422	1295.22	-0.01757	NO
19960104	1360.57	0.02806	NO	19960223	1342.56	-0.01385	NO	19960423	1296.44	0.00094	YES
19960105	1364.23	0.00269	YES	19960226	1330.57	-0.00893	YES	19960425	1303.7	0.0056	YES
19960108	1364.43	0.00015	YES	19960227	1333.86	0.00247	YES	19960426	1297.26	-0.00494	YES
19960109	1349.16	-0.01119	NO	19960228	1321.87	-0.00899	YES	19960429	1287.39	-0.00761	YES
19960110	1352.34	0.00236	YES	19960304	1325.86	0.00302	YES	19960430	1292.61	0.00405	YES
19960111	1369.66	0.01281	NO	19960305	1311.66	-0.01071	NO	19960502	1319.23	0.02059	NO
19960112	1375.91	0.00456	YES	19960306	1318.21	0.00499	YES	19960503	1318.59	-0.00049	YES
19960115	1376.8	0.00065	YES	19960307	1316.19	-0.00153	YES	19960507	1319.2	0.00046	YES
19960116	1371.64	-0.00375	YES	19960308	1308.97	-0.00549	YES	19960508	1310	-0.00697	YES
19960117	1371.06	-0.00042	YES	19960311	1263.66	-0.03462	NO	19960509	1307.47	-0.00193	YES
19960118	1354.21	-0.01229	NO	19960312	1266.55	0.00229	YES	19960510	1322.52	0.01151	NO
19960119	1375.03	0.01537	NO	19960313	1247.79	-0.01481	NO	19960513	1324.5	0.0015	YES
19960122	1389.43	0.01047	NO	19960314	1263.98	0.01297	NO	19960514	1319.26	-0.00396	YES
19960123	1388.87	-0.0004	YES	19960315	1266.93	0.00233	YES	19960515	1326.6	0.00556	YES
19960124	1378.3	-0.00761	YES	19960318	1277.01	0.00796	YES	19960516	1302.34	-0.01829	NO
19960125	1383.31	0.00363	YES	19960319	1284.08	0.00554	YES	19960517	1300.2	-0.00164	YES
19960126	1378.15	-0.00373	YES	19960320	1287.9	0.00297	YES	19960520	1289.23	-0.00844	YES
19960129	1376.45	-0.00123	YES	19960321	1293.51	0.00436	YES	19960521	1290.59	0.00105	YES
19960130	1393.34	0.01227	NO	19960322	1310.7	0.01329	NO	19960522	1266.52	-0.01865	NO
19960131	1410.33	0.01219	NO	19960325	1304.08	-0.00505	YES	19960523	1285.33	0.01485	NO
19960201	1399.6	-0.00761	YES	19960326	1297.66	-0.00492	YES	19960524	1299.55	0.01106	NO
19960202	1412.61	0.0093	YES	19960327	1288.13	-0.00734	YES	19960527	1311.2	0.00896	YES
19960206	1415.04	0.00172	YES	19960328	1282.76	-0.00417	YES	19960528	1308.2	-0.00229	YES
19960207	1408.73	-0.00446	YES	19960329	1289.73	0.00543	YES	19960529	1302.2	-0.00459	YES
19960208	1396.66	-0.00857	YES	19960401	1293.63	0.00302	YES	19960530	1311.91	0.00746	YES
19960209	1380.04	-0.0119	NO	19960402	1320.86	0.02105	NO	19960603	1294.11	-0.01357	NO
19960212	1360.71	-0.01401	NO	19960403	1342.5	0.01638	NO	19960604	1290.79	-0.00257	YES
19960213	1369.74	0.00664	YES	19960404	1333.5	-0.0067	YES	19960605	1276.61	-0.01099	NO
19960214	1379.2	0.00691	YES	19960405	1333.34	-0.00012	YES	19960606	1283.59	0.00547	YES
19960215	1380.87	0.00121	YES	19960409	1335.67	0.00175	YES	19960607	1284.34	0.00058	YES
19960216	1384.07	0.00232	YES	19960411	1331.02	-0.00348	YES	19960611	1259.75	-0.01915	NO
19960219	1385.62	0.00112	YES	19960417	1340.47	0.0071	YES	19960612	1243.77	-0.01269	NO
19960220	1384.96	-0.00048	YES	19960418	1331.14	-0.00696	YES	19960613	1247.05	0.00264	YES
19960221	1379.38	-0.00403	YES	19960419	1318.38	-0.00959	YES		TOTAL		73

Note : 1. Set Index is all stocks value weighted index.

2. Δ Set = $\frac{SET_d - SET_{d-}}{SET_d}$ Where SET_d = Closing Set Index at day ,d.

Table 4a : Discrete Time Trading Model Parameter Estimates for First (Most Active) and Fifth (Average Active) Volume Decile Portfolios.

This table presents the parameters estimated using the current model. Maximum likelihood estimation (MLE) is performed using the BFGS algorithm in the GAUSS statistical package. Standard errors are given parenthesis below the parameter estimates. Sample period is from Feb. 2, 1996 to Mar. 30, 1996.

1. The Trading Interval is 10 Minutes.
2. The Data Aggregation Method is "Net-Trade Tuple" or (NTM).

Panel A : First (Most Active) Decile for 10 Minutes Interval.

Ticker	α	δ	μ	γ	h_I	h_U	Market Capitalization (10^6)
BBC	0.6332 (0.1152)	0.2966 (0.1139)	0.4267 (0.0384)	0.6362 (0.0339)	0.9500 (0.1000)	0.3619 (0.0280)	24900.6906
BBL	0.6333 (0.2159)	0.3753 (0.1898)	0.2783 (0.0550)	0.7041 (0.0404)	0.9996 (0.0074)	0.5999 (0.0308)	240836.6758
BCHANG	0.6122 (0.1522)	0.6056 (0.1507)	0.3558 (0.0497)	0.5950 (0.0340)	0.1000 (0.0002)	0.4404 (0.0384)	2716.0500
BCP	0.2577 (0.5557)	0.5078 (0.7230)	0.0014 (0.1779)	0.5692 (0.0171)	0.6563 (0.6974)	0.4425 (0.0220)	17937.2944
BECL	0.6916 (0.2062)	0.4986 (0.1984)	0.2809 (0.0539)	0.6744 (0.0413)	0.0965 (0.1597)	0.5714 (0.0417)	33325.6000
BOA	0.7495 (0.5050)	0.6875 (0.2572)	0.2975 (0.0526)	0.6977 (0.0742)	0.0939 (0.2000)	0.5453 (0.0875)	23110.7880
CAPE	0.6374 (0.1279)	0.9500 (0.1000)	0.4696 (0.0414)	0.5613 (0.0343)	0.1000 (0.0018)	0.3767 (0.0498)	1029.1800
CMIC	0.3299 (0.1164)	0.7643 (0.1652)	0.4937 (0.0775)	0.5599 (0.0301)	0.4747 (0.0932)	0.6937 (0.0276)	16798.3744
CPICO	0.2500 (0.1120)	0.7500 (0.4820)	0.0010 (0.0079)	0.6839 (0.0164)	0.7500 (0.5822)	0.4404 (0.0210)	2866.2000
DEFT	0.6509 (0.3009)	0.1384 (0.1608)	0.2284 (0.0524)	0.6742 (0.0683)	0.9500 (0.1000)	0.3956 (0.0271)	8643.6800
EGCOMP	0.8048 (0.1574)	0.3473 (0.1551)	0.3057 (0.0467)	0.6722 (0.0460)	0.9639 (0.1246)	0.5603 (0.0372)	45146.4000
FBCB	0.4934 (0.1522)	0.6414 (0.2426)	0.4651 (0.0725)	0.5294 (0.0669)	0.4360 (0.1020)	0.4973 (0.0404)	28090.0000
FCI	0.2569 (0.1028)	0.5070 (0.1300)	0.0014 (0.0625)	0.6568 (0.0161)	0.6543 (0.6566)	0.3608 (0.0207)	10027.6000
ITF	0.2602 (0.8035)	0.9514 (0.1835)	0.0016 (0.0426)	0.7048 (0.0166)	0.7539 (0.9496)	0.3658 (0.0198)	5031.8221
KTB	0.6659 (0.3901)	0.5711 (0.2677)	0.3212 (0.0937)	0.6388 (0.0656)	0.5343 (0.1042)	0.6809 (0.0416)	179700.0700
KTT	0.5361 (0.1858)	0.1490 (0.1763)	0.3018 (0.0595)	0.6409 (0.0495)	0.0265 (0.2248)	0.5205 (0.0312)	27157.7110
NAVA	0.3790 (0.1650)	0.3244 (0.2677)	0.3467 (0.0812)	0.6189 (0.0370)	0.8912 (0.1503)	0.6711 (0.0284)	17538.7500

Table 4a : Discrete Time Trading Model Parameter Estimates for First (Most Active) and Fifth (Average Active) Volume Decile Portfolios.

This table presents the parameters estimated using the current model. Maximum likelihood estimation (MLE) is performed using the BFGS algorithm in the GAUSS statistical package. Standard errors are given parenthesis below the parameter estimates. Sample period is from Feb. 2, 1996 to Mar. 30, 1996.

1. The Trading Interval is 10 Minutes.
2. The Data Aggregation Method is "Net-Trade Tuple" or (NTM).

Panel A : First (Most Active) Decile for 10 Minutes Interval (Cont.)

Ticker	α	δ	μ	γ	h_I	h_U	Market Capitalization (10^6)
NPC	0.4523 (0.5797)	0.1716 (0.4273)	0.3195 (0.1465)	0.6237 (0.1340)	0.7882 (0.3637)	0.5659 (0.0283)	13240.1000
ONE	0.6774 (0.2082)	0.1536 (0.1282)	0.2424 (0.0542)	0.6802 (0.0448)	0.0213 (0.2714)	0.6179 (0.0279)	11075.2000
PHATRA	0.9142 (0.1027)	0.0469 (0.0879)	0.3289 (0.0421)	0.8834 (0.0578)	0.6159 (0.3572)	0.4194 (0.0233)	53317.6429
RR	0.2617 (0.5333)	0.9516 (0.7661)	0.0017 (0.0848)	0.6295 (0.0155)	0.7576 (0.2071)	0.4488 (0.0196)	1551.1500
SATTEL	0.8688 (0.1210)	0.9195 (0.1030)	0.2474 (0.0402)	0.5174 (0.0400)	0.1000 (0.0043)	0.7416 (0.0852)	14535.5000
SCB	0.3518 (0.1479)	0.4394 (0.2363)	0.2960 (0.0591)	0.7480 (0.0310)	0.1000 (0.0013)	0.5280 (0.0281)	111944.6579
SCCF	0.2827 (0.1500)	0.7514 (0.2100)	0.4711 (0.0890)	0.6425 (0.0333)	0.0859 (0.1296)	0.4567 (0.0323)	5803.2000
SITCA	0.6691 (0.1809)	0.1000 (0.0015)	0.2611 (0.0499)	0.7150 (0.0508)	0.8856 (0.1933)	0.5167 (0.0228)	9917.9500
SOMPR	0.2615 (0.6421)	0.9516 (0.7684)	0.0016 (0.0558)	0.6714 (0.0159)	0.7577 (0.6328)	0.4354 (0.0201)	1459.3390
SSI	0.7738 (0.3047)	0.3683 (0.1886)	0.2637 (0.0561)	0.6401 (0.0547)	0.9999 (0.0006)	0.5469 (0.0375)	13377.3000
SUSCO	0.4997 (0.1361)	0.5638 (0.2397)	0.2742 (0.0399)	0.7414 (0.0362)	0.9500 (0.1000)	0.2629 (0.0399)	1231.9200
TA	0.1918 (0.0802)	0.5485 (0.2260)	0.6542 (0.0830)	0.6392 (0.0218)	0.9495 (0.0634)	0.6750 (0.0227)	155098.7100
THAI	0.4684 (0.1177)	0.2042 (0.1239)	0.4301 (0.0539)	0.5458 (0.0302)	0.1000 (0.0022)	0.4560 (0.0290)	70994.0000
TMB	0.5632 (0.2892)	0.5346 (0.3498)	0.3082 (0.0821)	0.5827 (0.0711)	0.4655 (0.1586)	0.6925 (0.0354)	52490.8733
TMP	0.5055 (0.1497)	0.9877 (0.1420)	0.3062 (0.0442)	0.5904 (0.0330)	0.1000 (0.1000)	0.5739 (0.0484)	2026.6400
TYONG	0.2609 (0.6336)	0.9515 (0.8767)	0.0015 (0.0958)	0.5726 (0.0192)	0.7552 (0.3449)	0.4071 (0.0257)	12233.7235
WAT	0.3504 (0.1041)	0.8930 (0.1089)	0.4049 (0.0477)	0.7773 (0.0175)	0.9500 (0.1000)	0.2874 (0.0267)	9231.6491

Table 4a : Discrete Time Trading Model Parameter Estimates for First (Most Active) and Fifth (Average Active) Volume Decile Portfolios.

This table presents the parameters estimated using the current model. Maximum likelihood estimation (MLE) is performed using the BFGS algorithm in the GAUSS statistical package. Standard errors are given parenthesis below the parameter estimates. Sample period is from Feb. 2, 1996 to Mar. 30, 1996.

1. The Trading Interval is 10 Minutes.
2. The Data Aggregation Method is "Net-Trade Tuple" or (NTM).

Panel B : Fifth (Average Active) Decile for 10 Minutes Interval

Ticker	α	δ	μ	γ	h_I	h_U	Market Capitalization (10^6)
AFC	0.0999 (0.0570)	0.6658 (0.2817)	0.3011 (0.0630)	0.9073 (0.0105)	0.9500 (0.0000)	0.0460 (0.0085)	451.2360
AITCO	0.3597 (0.1400)	0.2319 (0.1540)	0.2221 (0.0400)	0.9461 (0.0174)	0.9500 (0.0000)	0.0938 (0.0120)	5013.9000
AMARIN	0.4587 (0.1039)	0.9500 (0.0000)	0.2892 (0.2374)	0.8719 (0.0423)	0.1000 (0.0033)	0.1143 (0.0433)	2226.4875
APRINT	0.2287 (0.0950)	0.7355 (0.2190)	0.1537 (0.0355)	0.9493 (0.0090)	0.9500 (0.0000)	0.0295 (0.0080)	510.3400
BKP	0.7969 (0.1126)	0.9830 (0.2721)	0.0004 (0.3334)	0.8864 (0.0265)	0.0084 (0.6064)	0.0432 (0.0112)	1273.2000
CATHAY	0.1116 (0.0880)	0.9500 (0.0000)	0.1851 (0.0750)	0.8610 (0.0120)	0.9500 (0.0000)	0.0850 (0.0130)	2213.5000
CENTEL	0.0916 (0.0633)	0.9500 (0.0000)	0.3368 (0.0710)	0.9198 (0.0075)	0.9500 (0.0010)	0.0360 (0.0094)	1616.4000
CPF	0.2889 (0.0988)	0.9500 (0.0000)	0.6933 (0.0784)	0.8178 (0.0166)	0.1000 (0.0002)	0.2001 (0.0197)	14762.4000
CTW	0.3120 (0.0910)	0.7960 (0.1580)	0.3250 (0.0390)	0.8520 (0.0160)	0.9500 (0.0000)	0.1180 (0.0160)	1692.3000
EWC	0.3350 (0.1120)	0.6280 (0.1940)	0.2900 (0.0410)	0.8239 (0.0190)	0.9500 (0.0000)	0.1360 (0.0170)	855.9414
HEMRAJ	0.5630 (0.2920)	0.0001 (0.0020)	0.1620 (0.0280)	0.9210 (0.0450)	0.1900 (3.5660)	0.2310 (0.0160)	11030.9378
JUTHA	0.6448 (0.3097)	0.9500 (0.2300)	0.4577 (0.1070)	0.8599 (0.0346)	0.1000 (0.0059)	0.1385 (0.0393)	481.1235
LOXLEY	0.1984 (0.0945)	0.9500 (0.0000)	0.8830 (0.0983)	0.7590 (0.0202)	0.1254 (0.0373)	0.2686 (0.0210)	16614.4000
N-PARK	0.0000 (0.1047)	0.0070 (0.7790)	0.4940 (0.0700)	0.8810 (0.0411)	0.4550 (0.6450)	0.1020 (0.0506)	19905.6590
NC	0.7874 (0.0798)	0.9500 (0.0000)	0.8293 (0.0397)	0.7438 (0.0374)	0.0097 (0.0137)	0.2098 (0.0405)	415.2000
ONPA	0.2775 (0.1098)	0.9500 (0.0000)	0.7908 (0.1289)	0.8418 (0.0175)	0.3711 (0.0638)	0.2443 (0.0251)	7782.0000

Table 4a : Discrete Time Trading Model Parameter Estimates for First (Most Active) and Fifth (Average Active) Volume Decile Portfolios.

This table presents the parameters estimated using the current model. Maximum likelihood estimation (MLE) is performed using the BFGS algorithm in the GAUSS statistical package. Standard errors are given parenthesis below the parameter estimates. Sample period is from Feb. 2, 1996 to Mar. 30, 1996.

1. The Trading Interval is 10 Minutes.
2. The Data Aggregation Method is "Net-Trade Tuple" or (NTM).

Panel B : Fifth (Average Active) Decile for 10 Minutes Interval (Cont.)

Ticker	α	δ	μ	γ	h_I	h_U	Market Capitalization (10^6)
PATKOL	0.2007 (0.0900)	0.3591 (0.2130)	0.2828 (0.0540)	0.9087 (0.0130)	0.9500 (0.1000)	0.0450 (0.0080)	225.0380
PE	0.1320 (0.0680)	0.5410 (0.2670)	0.3404 (0.0670)	0.9320 (0.0100)	0.9500 (0.0000)	0.1540 (0.0140)	3178.4000
PP	0.3640 (0.1007)	0.9500 (0.0000)	0.8896 (0.0585)	0.8211 (0.0192)	0.0554 (0.0157)	0.0900 (0.0142)	1910.5000
PRANDA	0.3061 (0.1040)	0.0003 (0.0220)	0.2350 (0.0370)	0.9360 (0.0100)	0.1170 (0.4343)	0.1560 (0.0100)	679.3500
PRG	0.2719 (0.1060)	0.1550 (0.0050)	0.1643 (0.0370)	0.9568 (0.0090)	0.9500 (0.0004)	0.1194 (0.0134)	1324.2000
SAFE	0.3487 (0.1076)	0.8053 (0.1299)	0.3400 (0.0761)	0.8849 (0.0129)	0.7261 (0.1718)	0.0886 (0.0163)	958.5444
SAWANG	0.1407 (0.7986)	0.9520 (0.9970)	0.0001 (0.0108)	0.9395 (0.0084)	0.1672 (0.4214)	0.0880 (0.0103)	607.6800
SSC	0.2196 (0.0610)	0.7351 (0.2170)	0.2848 (0.0130)	0.8930 (0.0120)	0.9500 (0.0000)	0.0621 (0.0120)	13207.4800
STANLEY	0.4853 (0.1048)	0.9500 (0.0000)	0.7179 (0.0522)	0.7840 (0.0209)	0.1000 (0.0000)	0.2030 (0.0236)	4029.2730
SVH	0.2436 (0.1224)	0.1623 (0.2956)	0.1956 (0.0504)	0.9215 (0.0142)	0.6780 (0.5038)	0.0743 (0.0134)	1246.8000
SVOA	0.2660 (0.1530)	0.4708 (0.2570)	0.2150 (0.0610)	0.8540 (0.0160)	0.9500 (0.0000)	0.1210 (0.0190)	1386.3000
THORES	0.2990 (0.0960)	0.7200 (0.1780)	0.2500 (0.0380)	0.8670 (0.0140)	0.9500 (0.0000)	0.0840 (0.0150)	2079.0000
TPC	0.8182 (0.1175)	0.9500 (0.0000)	0.5528 (0.0595)	0.7498 (0.0442)	0.1000 (0.0000)	0.3277 (0.0730)	11517.6250
TRU	0.0040 (0.2414)	0.9887 (0.2820)	0.0082 (0.5585)	0.8185 (0.0135)	0.3607 (0.6499)	0.3394 (0.0184)	3847.6000
TVI	0.2001 (0.0510)	0.9500 (0.0000)	0.1690 (0.0490)	0.9259 (0.0090)	0.9500 (0.0020)	0.0930 (0.0150)	449.3490
UFC	0.1947 (0.0810)	0.3459 (0.2096)	0.2852 (0.0470)	0.9452 (0.0107)	0.9500 (0.0000)	0.0554 (0.0088)	267.4000
VIBHA	0.0692 (0.0470)	0.9500 (0.0001)	0.2200 (0.0666)	0.9373 (0.0080)	0.9500 (0.0001)	0.0437 (0.0070)	472.9345

Table 4b : Discrete Time Trading Model Parameter Estimates for High and Low SET-50 Portfolios.

This table presents the parameters estimated using the current model. Maximum likelihood estimation (MLE) is performed using the BFGS algorithm in the GAUSS statistical package. Standard errors are given parenthesis below the parameter estimates. Sample period is from Feb. 2, 1996 to Mar. 30, 1996.

1. The Trading Interval is 10 Minutes.
2. The Data Aggregation Method is "Net-Trade Tuple" or (NTM).

Panel A: High Trading volume SET-50 portfolio.

TICKER	α	δ	μ	γ	h_I	h_U	Market Capitalization (10˘)
BBC	0.6332	0.2966	0.4267	0.6362	0.9500	0.3619	24900.6906
	(0.1152)	(0.1139)	(0.0384)	(0.0339)	(0.0100)	(0.0280)	
BBL	0.6333	0.3753	0.2783	0.7041	0.9996	0.5999	240836.6758
	(0.2159)	(0.1898)	(0.0550)	(0.0404)	(0.0074)	(0.0308)	
BCP	0.2577	0.5078	0.0014	0.5692	0.6563	0.4425	17937.2944
	(0.5557)	(0.7230)	(0.1779)	(0.0171)	(0.0697)	(0.0220)	
BOA	0.7495	0.6875	0.2975	0.6977	0.0939	0.5453	23110.7880
	(0.5050)	(0.2572)	(0.0526)	(0.0742)	(0.2000)	(0.0875)	
CMIC	0.3299	0.7643	0.4937	0.5599	0.4747	0.6937	16798.3744
	(0.1164)	(0.1652)	(0.0775)	(0.0301)	(0.0932)	(0.0276)	
EGCOMP	0.8048	0.3473	0.3057	0.6722	0.9639	0.5603	45146.4000
	(0.1574)	(0.1551)	(0.0467)	(0.0460)	(0.1246)	(0.0372)	
FBCB	0.4934	0.6414	0.4651	0.5294	0.4360	0.4973	28090.0000
	(0.1522)	(0.2426)	(0.0725)	(0.0669)	(0.1020)	(0.0404)	
KTB	0.6659	0.5711	0.3212	0.6388	0.5343	0.6809	179700.0700
	(0.3901)	(0.2677)	(0.0937)	(0.0656)	(0.1042)	(0.0416)	
NAVA	0.3790	0.3244	0.3467	0.6189	0.8912	0.6711	17538.7500
	(0.1650)	(0.2677)	(0.0812)	(0.0370)	(0.1503)	(0.0284)	
NPC	0.2733	0.6683	0.4487	0.5435	0.4635	0.5956	13240.1000
	(0.1481)	(0.2711)	(0.1133)	(0.0356)	(0.1232)	(0.0295)	
ONE	0.2573	0.7543	0.0013	0.5938	0.5926	0.5926	11075.2000
	(0.1137)	(0.0830)	(0.0469)	(0.0172)	(0.0227)	(0.0227)	
SATTEL	0.8688	0.9195	0.2474	0.5174	0.9500	0.7416	14535.5000
	(0.1210)	(0.1030)	(0.0402)	(0.0400)	(0.0043)	(0.0852)	
SSI	0.7738	0.3683	0.2637	0.6401	0.9500	0.5469	13377.3000
	(0.3047)	(0.1886)	(0.0561)	(0.0547)	(0.0006)	(0.0375)	
TA	0.1918	0.5485	0.6542	0.6392	0.9495	0.6750	155098.7100
	(0.0802)	(0.2260)	(0.0830)	(0.0218)	(0.0634)	(0.0227)	
THAI	0.4684	0.2042	0.4301	0.5458	0.9500	0.4560	70994.0000
	(0.1177)	(0.1239)	(0.0539)	(0.0302)	(0.0022)	(0.0290)	
TMB	0.5632	0.5346	0.3082	0.5827	0.4655	0.6925	52490.8733
	(0.2892)	(0.3498)	(0.0821)	(0.0711)	(0.1586)	(0.0354)	
TYONG	0.5346	0.6417	0.5346	0.5727	0.9963	0.4055	12233.7235
	(0.3498)	(0.0359)	(0.3498)	(0.0145)	(0.1012)	(0.0298)	

Table 4b : Discrete Time Trading Model Parameter Estimates for High and Low SET-50 Portfolios.

This table presents the parameters estimated using the current model. Maximum likelihood estimation (MLE) is performed using the BFGS algorithm in the GAUSS statistical package. Standard errors are given parenthesis below the parameter estimates. Sample period is from Feb. 2, 1996 to Mar. 30, 1996.

1. The Trading Interval is 10 Minutes.
2. The Data Aggregation Method is "Net-Trade Tuple" or (NTM).

Panel B : Low Trading volume SET-50 portfolio.

TICKER	α	δ	μ	γ	h_I	h_U	Market Capitalization (10^6)
AA	0.2214	0.4907	0.2496	0.9303	0.9500	0.0574	23479.7000
	(0.1013)	(0.2243)	(0.0523)	(0.0121)	(0.0020)	(0.0101)	
ACL	0.2595	0.9513	0.0015	0.7048	0.7526	0.3325	13342.9611
	(0.1138)	(0.0145)	(0.0759)	(0.0155)	(0.0963)	(0.0175)	
ADVANC	0.6791	0.8093	0.2890	0.7369	0.9500	0.3788	109079.1000
	(0.1384)	(0.1226)	(0.0436)	(0.0273)	(0.0010)	(0.0414)	
AST	0.2606	0.9515	0.0016	0.6480	0.7557	0.4017	9903.4000
	(0.0907)	(0.6867)	(0.0578)	(0.0161)	(0.0431)	(0.0204)	
B-LAND	0.7577	0.0001	0.1471	0.6794	0.0127	0.2945	18864.0000
	(0.5973)	(0.0156)	(0.1157)	(0.1188)	(0.0145)	(0.0206)	
JASMIN	0.2063	0.9500	0.7252	0.6893	0.7893	0.6073	35801.9520
	(0.1376)	(0.0100)	(0.1566)	(0.0277)	(0.0629)	(0.0272)	
LOXLEY	0.1984	0.9500	0.8830	0.7590	0.1254	0.2686	16614.4000
	(0.0945)	(0.0100)	(0.0983)	(0.0202)	(0.0373)	(0.0210)	
MDX	0.6626	0.9489	0.4790	0.6210	0.0516	0.5954	6958.1322
	(0.1098)	(0.0516)	(0.0651)	(0.0308)	(0.0850)	(0.0583)	
NTS	0.3062	0.8320	0.3894	0.6727	0.0226	0.4776	5120.4150
	(0.2687)	(0.1913)	(0.1867)	(0.0328)	(0.1836)	(0.0547)	
PHATRA	0.9142	0.0469	0.3289	0.8834	0.6159	0.4194	53317.6429
	(0.1027)	(0.0879)	(0.0421)	(0.0578)	(0.3572)	(0.0233)	
PTTEP	0.2619	0.9506	0.0016	0.7209	0.7547	0.3679	97563.2000
	(0.1518)	(0.0253)	(0.0821)	(0.0153)	(0.6277)	(0.0171)	
SCB	0.2573	0.5046	0.0013	0.7137	0.2499	0.4897	111944.6579
	(0.0787)	(0.1213)	(0.0358)	(0.0166)	(0.1424)	(0.0213)	
SCC	0.8147	0.0100	0.2246	0.9625	0.5730	0.3155	148762.8000
	(0.0903)	(0.0040)	(0.0226)	(0.0243)	(0.0661)	(0.0184)	
SCCC	0.2712	0.5460	0.4416	0.7560	0.9500	0.3118	42386.0346
	(0.0938)	(0.1887)	(0.0587)	(0.0186)	(0.0010)	(0.0221)	
SHIN	0.4437	0.3552	0.2821	0.7944	0.9500	0.3250	88954.8660
	(0.1248)	(0.0626)	(0.0430)	(0.0242)	(0.0010)	(0.0233)	
TPIPL	0.3719	0.5318	0.5092	0.5997	0.0203	0.4657	35903.0875
	(0.0984)	(0.1616)	(0.0607)	(0.0241)	(0.0731)	(0.0278)	
UAF	0.2599	0.7538	0.0015	0.6357	0.7538	0.3609	8895.7481
	(0.1048)	(0.0801)	(0.0644)	(0.0160)	(0.0801)	(0.0164)	

Table 5 : Summary Parameter Estimate Statistics.

This table presents means, medians and sample standard deviation of First/Fifth volume decile and High/Low SET-50 portfolios.Estimate parameters presented in Table 4a and 4b.

Parameter Number in Sample	First Decile 34	Fifth Decile 34	High SET-50	Low SET-50
α = The probability that an information event occurance				
Mean	0.5057	0.3066	0.5001	0.4204
Median	0.5026	0.2719	0.4934	0.2712
Std. Dev.	0.2058	0.2145	0.2316	0.2424
δ = The probability of a low signal				
Mean	0.5457	0.7055	0.5385	0.6394
Median	0.5416	0.8053	0.5485	0.8093
Std. Dev.	0.3012	0.3540	0.1958	0.3641
μ = The probability that trader comes from an informed trader				
Mean	0.2762	0.3504	0.3122	0.2915
Median	0.2997	0.2852	0.3082	0.2821
Std. Dev.	0.1669	0.2486	0.1782	0.2624
γ = The probability that an uninformed trader want to be a seller				
Mean	0.6476	0.8763	0.6036	0.7358
Median	0.6405	0.8849	0.5938	0.7137
Std. Dev.	0.0760	0.0607	0.0577	0.1048
h_I = Probability that an informed trader owns the stock				
Mean	0.5416	0.5838	0.6134	0.5575
Median	0.6553	0.7261	0.5343	0.7526
Std. Dev.	0.3927	0.4442	0.3576	0.3876
h_U = Probability that an uninformed trader already owns the stock				
Mean	0.5046	0.1285	0.5740	0.3806
Median	0.5070	0.1020	0.5926	0.3679
Std. Dev.	0.1222	0.0825	0.1121	0.1293

Table 6 : Non-Parametric Tests Results.

Panel A : Kolmogorov-Smirnov (KS) One-Sample Test on Parameters.

The Kolmogorov-Smirnov statistic is used to test :

H_0 : There is no difference in the expected value of the estimated parameter for each stock across its own decile and any observed differences are merely chance variations to be expected in a ramdom sample from the Poisson population.

H_1 : The frequencies of the estimated parameter are not all equal.

Parameter	First Decile	Fifth Decile	High SET-50	Low SET-50
	Test Statistic	Test Statistic	Test Statistic	Test Statistic
α	0.433	0.538	0.429	0.909
δ	0.766	1.183	0.192	0.980
μ	1.057	1.151	0.721	0.968
γ	1.687 **	1.967 **	1.002	0.673
h_I	1.744 **	1.701 **	0.814	1.127
h_u	1.253	0.665	0.925	0.407

* * Reject the null hypothesis at 95% confident interval

Panel B : Chi Square and Mann-Whitney Test Two- Sample Tests on Parameters

The χ^2 statistic on the *dispersion* is used to test :

H_0 : The proportion of estimated parameters from each stocks in high SET-50 and low SET-50 are drawn from the same population.

H_1 : The proportion of estimated parameters from each stocks in high SET-50 and low SET-50 are *not* drawn from the same population.

The Mann-Whitney statistic on *medians* is used to test :

H_0 : The estimated parameters frequencies in the first (high SET-50) decile are stochastically *equal* than the frequencies in the fifth decile (low SET-50).

H_1 : The estimated parameters frequencies in the first (high SET-50) decile are stochastically *larger* than the estimated parameters frequencies in the fifth decile (low SET-50).

Parameter	Volume Decile		SET-50	
	χ^2 Test	Mann-Whitney	χ^2 Test(SET-50)	Mann-Whitney(SET-50)
	Test Statistic	Pairwise Comparison 1 to 5	Test Statistic	Pairwise Comparison High to Low
α	46.6015 **	3.5460 **	28.1773 **	0.8956
δ	57.6298 **	-2.6416 **	31.8259 **	-1.2917
μ	39.0689 **	-0.2629	33.2171 **	0.4995
γ	6.2301 **	-6.7649 **	8.1254 **	-3.9093 **
h_I	42.1213 **	-1.3102	28.6379 **	-0.1207
h_u	9.5615 **	6.9445 **	20.5971 **	3.7027 **

* * Reject the null hypothesis at 95% confident interval

Table 7 : A sample data and p-value calculation for KTB include number of buy, sell and no trade event, with indicative probability,and number of acceptable case.

Date	# Buy	# Sell	# No Trade	p-value	# of Cases p-value $\geq .01/d$
1	14	10	3	0.0082	1
2	7	13	7	0.0140	1
3	15	7	5	0.0052	1
4	19	6	2	0.0001	0
5	12	10	5	0.0250	1
6	17	7	3	0.0011	1
7	12	10	5	0.0250	1
8	7	10	10	0.0051	1
9	14	9	4	0.0109	1
10	9	10	8	0.0189	1
11	9	10	8	0.0189	1
12	8	9	10	0.0058	1
13	11	11	5	0.0295	1
14	9	13	5	0.0244	1
15	8	12	7	0.0210	1
16	14	10	3	0.0082	1
17	6	13	8	0.0071	1
18	6	12	9	0.0054	1
19	9	12	6	0.0282	1
20	8	13	6	0.0212	1
21	8	15	4	0.0106	1
22	2	13	12	0.0000	0
23	5	16	6	0.0027	1
24	3	17	7	0.0003	0
25	11	12	4	0.0231	1
26	10	12	5	0.0293	1
27	12	10	5	0.0250	1
28	16	7	4	0.0028	1
29	5	14	8	0.0033	1
30	18	7	2	0.0003	0
			Bonferroni	**0.9873**	**26**

1. The trading interval is 10 mintues. Hence, there are 27 intervals in a trading day.
2. p-value is calculate from equation (13).
3. d = No. of day

Table 8a : Summary of Probability,Bonferroni Bound and Acceptable Cases for Stocks in Table 4a

Panel A : First (Most Active) Decile for 10 Minute Interval

Ticker	Probability of			# of Cases (1) *p* -value >.01/d	Bonferroni(2) Lower Bound	# of Cases (3) p_i<.05/n
	Buy	Sell	No Trade			
BBC	0.4555	0.2482	0.2963	17	0.99553	0
BBL	0.3539	0.4140	0.2321	27	0.98959	0
BCHANG	0.4027	0.2049	0.3924	24	0.99158	0
BCP	0.4309	0.2519	0.3173	27	0.98925	0
BECL	0.3597	0.3198	0.3204	25	0.99068	0
BOA	0.3046	0.3100	0.3854	23	0.99052	0
CAPE	0.3074	0.1482	0.5444	28	0.99125	0
CMIC	0.4068	0.3842	0.2089	26	0.98953	0
CPICO	0.3161	0.3012	0.3827	19	0.99461	0
DEFT	0.4055	0.2476	0.3469	27	0.99009	0
EGCOMP	0.4077	0.3663	0.2260	25	0.99211	0
FBCB	0.4449	0.2670	0.2881	24	0.99110	0
FCI	0.3432	0.2370	0.4197	22	0.99055	0
ITF	0.2951	0.2580	0.4469	26	0.98879	0
KTB	0.3757	0.4072	0.2171	26	0.98731	0
KTT	0.4387	0.2803	0.2810	27	0.99126	0
NAVA	0.4198	0.3987	0.1815	28	0.98670	0
NPC	0.4416	0.3215	0.2369	26	0.98723	0
ONE	0.4063	0.3518	0.2419	27	0.99018	0
PHATRA	0.3681	0.2678	0.3641	25	0.99107	0
RR	0.3704	0.2827	0.3469	26	0.98992	0
SATTEL	0.3962	0.3012	0.3026	28	0.99015	0
SCB	0.2841	0.3538	0.3620	27	0.99085	0
SCCF	0.3430	0.2630	0.3940	24	0.98875	0
SITCA	0.4099	0.3049	0.2852	28	0.99100	0
SOMPR	0.3285	0.2925	0.3790	27	0.99002	0
SSI	0.4154	0.3538	0.2309	26	0.98958	0
SUSCO	0.2829	0.2455	0.4716	23	0.99364	0
TA	0.3722	0.4426	0.1852	24	0.98978	0
THAI	0.5230	0.1988	0.2782	25	0.99001	0
TMB	0.4256	0.3767	0.1977	27	0.98788	0
TMP	0.3481	0.2864	0.3655	23	0.99060	0
TYONG	0.4273	0.2333	0.3395	28	0.98722	0
WAT	0.2063	0.3184	0.4753	23	0.99218	0
Mean	0.3770	0.3012	0.3219		0.9903	
Median	0.3859	0.2969	0.3189		0.9902	

Note : (1) In sample period , the number of days in which p-value is greater than 0.1 % . d=number of days

(2) Bonferroni Lower Bound is Calculated from Equation (15).

(3) # of Case Break Bonferroni Lower Bound at 95 % Confident Level. n=total number of stocks.

Table 8a : Summary of Probability, Bonferroni Bound and Acceptable Cases for Stocks in Table 4a

Panel B : Fifth (Average Active) Decile for 10 Minute Interval

Ticker	Probability of			# of Cases (1) p -value >.01/d	Bonferroni(2) Lower Bound	# of Cases (3) p_i<.05/n
	Buy	Sell	No Trade			
AFC	0.1000	0.0605	0.8395	28	0.95845	0
AITCO	0.1111	0.1001	0.7889	26	0.98180	0
AMARIN	0.1111	0.0864	0.8025	30	0.96339	0
APRINT	0.0580	0.0529	0.8889	28	0.94024	0
BKP	0.1136	0.0383	0.8481	30	0.95114	0
CATHAY	0.1361	0.0923	0.7715	28	0.97477	0
CENTEL	0.0778	0.0630	0.8593	28	0.96134	0
CPF	0.1457	0.1309	0.7235	27	0.98895	0
CTW	0.1537	0.1711	0.6753	23	0.98818	0
EWC	0.1951	0.1622	0.6427	24	0.98956	0
HEMRAJ	0.1630	0.1933	0.6437	25	0.98348	0
JUTHA	0.0988	0.0839	0.8173	30	0.96469	0
LOXLEY	0.1988	0.1901	0.6111	23	0.99013	0
N-PARK	0.1190	0.0899	0.7911	28	0.97562	0
NC	0.0889	0.0605	0.8506	26	0.96537	0
ONPA	0.1235	0.2420	0.6346	29	0.98548	0
PATKOL	0.1225	0.0590	0.8185	25	0.97496	0
PE	0.0856	0.1614	0.7530	27	0.97938	0
PP	0.1210	0.0679	0.8111	30	0.97117	0
PRANDA	0.1313	0.1355	0.7332	25	0.98616	0
PRG	0.0790	0.1161	0.8049	28	0.97940	0
SAFE	0.1245	0.1384	0.7371	26	0.98544	0
SAWANG	0.0605	0.0827	0.8568	30	0.96195	0
SSC	0.1169	0.0980	0.7852	26	0.98390	0
STANLEY	0.1407	0.1037	0.7555	28	0.98649	0
SVH	0.1147	0.0704	0.8148	28	0.97376	0
SVOA	0.1679	0.1243	0.7077	28	0.98479	0
THORES	0.1440	0.1212	0.7348	24	0.98415	0
TPC	0.1370	0.1346	0.7284	27	0.98551	0
TRU	0.1815	0.2778	0.5407	29	0.98743	0
TVI	0.0716	0.1170	0.8114	26	0.98408	0
UFC	0.0880	0.0687	0.8433	26	0.96387	0
VIBHA	0.0617	0.0556	0.8827	28	0.93993	0
Mean	0.1195	0.1136	0.7669		0.9750	
Median	0.1190	0.1001	0.7889		0.9794	

Note : (1) In sample period , the number of days in which p-value is greater than 0.1 % . d=number of days.

(2) Bonferroni Lower Bound is Calculated from Equation (15).

(3) # of Case Break Bonferroni Lower Bound at 95 % Confident Level. n=total number of stocks.

Table 8b : Summary of Probability, Bonferroni Bound and Acceptable Cases For Stocks in Table 4b.

Panel A : High (Trading Volume) SET-50 P-Value.

Ticker	Probability of			# of Cases (1) *p* -value >.01/d	Bonferroni (2) Lower Bound	# of Cases (3) p_i<.05/n
	Buy	Sell	No Trade			
BBC	0.4555	0.2482	0.2963	17	0.99553	0
BBL	0.3539	0.4140	0.2321	27	0.98959	0
BCP	0.4309	0.2519	0.3173	27	0.98925	0
BOA	0.3046	0.3100	0.3854	23	0.99052	0
CMIC	0.4068	0.3842	0.2089	26	0.98953	0
EGCOMP	0.4077	0.3663	0.2260	25	0.99211	0
FBCB	0.4449	0.2670	0.2881	24	0.99110	0
KTB	0.3757	0.4072	0.2171	26	0.98731	0
NAVA	0.4198	0.3987	0.1815	28	0.98670	0
NPC	0.4416	0.3215	0.2369	26	0.98723	0
ONE	0.4063	0.3518	0.2419	27	0.99018	0
SATTEL	0.3962	0.3012	0.3026	28	0.99015	0
SSI	0.4154	0.3538	0.2309	26	0.98958	0
TA	0.3722	0.4426	0.1852	24	0.98978	0
THAI	0.5230	0.1988	0.2782	25	0.99001	0
TMB	0.4256	0.3767	0.1977	27	0.98788	0
TYONG	0.4273	0.2333	0.3395	24	0.98722	0
Mean	0.4122	0.3310	0.2568		0.9896	
Median	0.4154	0.3518	0.2369		0.9896	

Panel B : Low (Trading Volume) SET-50 P-Value.

Ticker	Probability of			# of Cases (1) *p* -value >.01/d	Bonferroni (2) Lower Bound	# of Cases (3) p_i<.05/n
	Buy	Sell	No Trade			
AA	0.0940	0.0776	0.8284	27	0.97396	0
ACL	0.2951	0.2346	0.4704	25	0.98992	0
ADVANC	0.2489	0.3832	0.3679	25	0.99041	0
AST	0.3519	0.2605	0.3877	22	0.99314	0
B-LAND	0.3963	0.1778	0.4259	30	0.98839	0
JASMIN	0.2642	0.4741	0.2617	25	0.99242	0
LOXLEY	0.1988	0.1901	0.6111	23	0.99013	0
MDX	0.2749	0.2679	0.4572	23	0.99146	0
NTS	0.3083	0.2852	0.4065	25	0.98983	0
PHATRA	0.3681	0.2678	0.3641	25	0.99107	0
PTTEP	0.2790	0.2654	0.4556	28	0.99117	0
SCB	0.2841	0.3538	0.3620	27	0.99085	0
SCC	0.2136	0.2481	0.5383	22	0.99246	0
SCCC	0.2691	0.2729	0.4580	20	0.99216	0
SHIN	0.2605	0.2703	0.4691	25	0.99112	0
TPIPL	0.4131	0.2284	0.3584	24	0.99153	0
UAF	0.3642	0.2296	0.4062	27	0.99048	0
Mean	0.2873	0.2640	0.4487		0.9900	
Median	0.2790	0.2654	0.4259		0.9911	

Note : (1) In sample period , the number of days in which *p* -value is greater than 0.1 %. d=number of days.

(2) Bonferroni Bound is Calculate from Equation (15).

(3) # of Case Break Bonferroni Lower Bound at 95% Confident Level. n=total number of stocks.

Table 9a : Robustness check for the 1st & 5th Volume Decile and High & Low SET-50 Volume Portfolios. The Trading Intervals are for 5,10 and 15 minutes. The Statistical Aggregation is Based on " Net Trade-Tuples Method ". (Sample period is Feb - Mar, 96.)

		1st Decile			5th Decile			High SET-50			Low SET-50		
		5	10	15	5	10	15	5	10	15	5	10	15
α	Mean	0.54323	0.50573	0.43292	0.20216	0.30660	0.28720	0.52671	0.50009	0.46821	0.54042	0.42038	0.37197
	Median	0.54645	0.50260	0.27151	0.21315	0.27192	0.26119	0.55456	0.49340	0.39166	0.50351	0.27116	0.26652
	Std. Dev.	0.18539	0.20583	0.23424	0.14915	0.21451	0.15934	0.18530	0.23164	0.25029	0.16224	0.24245	0.20645
δ	Mean	0.56818	0.54567	0.65016	0.55784	0.70553	0.52930	0.54801	0.53852	0.54557	0.37571	0.63944	0.79229
	Median	0.58173	0.54157	0.89330	0.55180	0.80530	0.64783	0.53748	0.54852	0.48008	0.32010	0.80931	0.95123
	Std. Dev.	0.33151	0.30122	0.35440	0.35252	0.35399	0.38940	0.23642	0.19580	0.36669	0.33853	0.36406	0.23122
μ	Mean	0.30961	0.27615	0.20537	0.30105	0.35043	0.22691	0.26268	0.31219	0.25475	0.26965	0.29154	0.20723
	Median	0.25460	0.29966	0.10630	0.20035	0.28521	0.24738	0.24102	0.30819	0.28962	0.22194	0.28213	0.28909
	Std. Dev.	0.15541	0.16693	0.22910	0.23335	0.24862	0.17132	0.14372	0.17823	0.24868	0.16220	0.26240	0.20623
γ	Mean	0.71922	0.64760	0.60401	0.93245	0.87628	0.87072	0.70352	0.60361	0.57838	0.83842	0.73575	0.67531
	Median	0.71013	0.64051	0.60937	0.94102	0.88494	0.87327	0.69684	0.59377	0.57200	0.84580	0.71365	0.68506
	Std. Dev.	0.08158	0.07597	0.08785	0.03611	0.06071	0.05379	0.05567	0.05769	0.08938	0.04642	0.10482	0.09204
h_I	Mean	0.55907	0.54157	0.62739	0.61629	0.58376	0.75239	0.58158	0.61337	0.60625	0.70879	0.55749	0.56899
	Median	0.69316	0.65530	0.75761	0.79963	0.72608	0.80399	0.75013	0.53434	0.75753	1.00000	0.75260	0.75597
	Std. Dev.	0.41203	0.39270	0.28483	0.41419	0.44416	0.28901	0.41224	0.35755	0.30015	0.39875	0.38764	0.37799
h_U	Mean	0.35504	0.50460	0.57470	0.06586	0.12850	0.15001	0.38698	0.57402	0.65085	0.23438	0.38057	0.46777
	Median	0.35569	0.50700	0.53663	0.05382	0.10200	0.12943	0.38929	0.59255	0.67360	0.21533	0.36793	0.48902
	Std. Dev.	0.11511	0.12224	0.12107	0.04707	0.08255	0.09598	0.11390	0.11215	0.11268	0.09068	0.12926	0.16676

$P^L(S)$	0.349386	0.3860935	0.4046827	0.2284574	0.2777099	0.2717033	0.3535035	0.4298033	0.4349831	0.3346455	0.3609025	0.3683397
$P^L(B)$	0.1938477	0.2550847	0.3146655	0.0472141	0.0803648	0.0999451	0.2186006	0.272641	0.3142123	0.11801	0.1872106	0.2574045
$P^L(N)$	0.4567663	0.3588218	0.2806518	0.7243285	0.6419253	0.6283516	0.4278959	0.2975557	0.2508046	0.5473446	0.4518869	0.3742558
$P^H(S)$	0.1762924	0.236539	0.2758356	0.0429233	0.0731429	0.1009785	0.200734	0.2383153	0.2805409	0.1435203	0.1983719	0.2504279
$P^H(B)$	0.5034577	0.5312347	0.5200355	0.3482641	0.4307948	0.3268551	0.4812806	0.584831	0.5689623	0.38766	0.4787506	0.4646345
$P^H(N)$	0.3202499	0.2322263	0.2041289	0.6088126	0.4960623	0.5721665	0.3179853	0.1768537	0.1504968	0.4688198	0.3228775	0.2849376
$P^O(S)$	0.2553519	0.326779	0.3471245	0.0614112	0.112602	0.1306167	0.2722482	0.3464842	0.3764386	0.1965089	0.2800044	0.3158898
$P^O(B)$	0.28078	0.35240	0.39599	0.06755	0.12372	0.12928	0.29648	0.39639	0.42162	0.16158	0.26425	0.32469
$P^O(N)$	0.4638681	0.320821	0.2568855	0.8710388	0.763678	0.7401033	0.4312718	0.2571258	0.2019414	0.6419111	0.4557456	0.3594202

Table 9b : Robustness check for the 1st & 5th Volume Decile and High & Low SET-50 Volume Portfolios. The Trading Intervals are for 5,10 and 15 minute. The Statistical Aggregation is Based on " Net Trading Volume Method ". (Sample period is Feb - Mar 96.)

		1st Decile			5th Decile			High SET-50			Low SET-50		
		5	10	15	5	10	15	5	10	15	5	10	15
α	Mean	0.50224	0.46467	0.47498	0.19778	0.24479	0.25235	0.52840	0.49801	0.58006	0.44872	0.40997	0.29678
	Median	0.51067	0.34910	0.39839	0.20527	0.22330	0.25926	0.53343	0.50763	0.59232	0.42657	0.29348	0.26495
	Std. Dev.	0.16993	0.23923	0.24440	0.14338	0.16038	0.12913	0.16799	0.24900	0.24332	0.19160	0.21793	0.10791
δ	Mean	0.64174	0.55988	0.58579	0.55548	0.59197	0.62572	0.65345	0.41210	0.32601	0.30480	0.76967	0.87687
	Median	0.73083	0.76771	0.93981	0.51796	0.70920	0.71433	0.73909	0.31831	0.18663	0.26104	0.90357	0.95193
	Std. Dev.	0.33686	0.38966	0.43123	0.34893	0.37718	0.35332	0.32354	0.36430	0.38223	0.33336	0.25193	0.17579
μ	Mean	0.28062	0.20142	0.17649	0.30088	0.26221	0.21620	0.25783	0.23717	0.26045	0.25468	0.27128	0.11263
	Median	0.25815	0.27193	0.00390	0.19959	0.26794	0.23819	0.25422	0.28530	0.31384	0.22733	0.30034	0.00191
	Std. Dev.	0.15021	0.16705	0.19883	0.23665	0.19563	0.17388	0.15513	0.16697	0.19137	0.11434	0.24495	0.18312
γ	Mean	0.67333	0.61522	0.55133	0.92908	0.88379	0.84362	0.64122	0.59847	0.55377	0.81909	0.67170	0.62086
	Median	0.67063	0.61612	0.54424	0.93786	0.88910	0.84628	0.63659	0.61094	0.53353	0.81625	0.68207	0.60910
	Std. Dev.	0.09064	0.07470	0.08909	0.03662	0.05633	0.06674	0.08780	0.07222	0.10985	0.06462	0.08174	0.09949
h_I	Mean	0.54019	0.64085	0.66939	0.64689	0.76119	0.80359	0.39765	0.49885	0.71199	0.84853	0.58842	0.67619
	Median	0.75214	0.76140	0.76493	0.86509	0.98460	1.00000	0.19641	0.39787	0.80229	1.00000	0.75808	0.76221
	Std. Dev.	0.43958	0.32945	0.30854	0.40788	0.32617	0.27316	0.39891	0.33648	0.32953	0.26840	0.40537	0.28225
h_U	Mean	0.43279	0.57364	0.72776	0.06805	0.11598	0.16425	0.51873	0.68186	0.81628	0.25953	0.44312	0.58206
	Median	0.41507	0.53148	0.72812	0.05329	0.09518	0.13826	0.51402	0.71253	0.83834	0.24989	0.43016	0.57880
	Std. Dev.	0.16943	0.16599	0.13359	0.04758	0.08047	0.10944	0.14483	0.13684	0.09479	0.10072	0.17839	0.19183

Table 10a : Speed of Adjustment Comparison when a short sale is prohibited.
(i.e. $0<h_I<1$ and $0<h_U<1$). One can calculate the speed of adjustment by using the mean values of the estimates parameter from Table 9a in equation (15).
Average γ Values are in Parenthesis.

Portfolio	5 Min	10 Min	15 Min
For First Decile			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.1100	0.0665	0.0314
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.0307	0.0221	0.0146
Average γ Values	(0.7192)	(0.6476)	(0.6040)
For Fifth Decile			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.3377	0.2919	0.1299
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.1496	0.0656	0.0704
Average γ Values	(0.9325)	(0.8763)	(0.8707)
For high volume SET-50 portfolios			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.0751	0.0721	0.0438
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.0224	0.0340	0.0248
Average γ Values	(0.7035)	(0.6036)	(0.5784)
For low volume SET-50 portfolios			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.1468	0.1049	0.0422
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.0538	0.0232	0.0119
Average γ Values	(0.8384)	(0.7358)	(0.6753)

Note: *I* $_P$ψ (*P* ψข) = Σ P$^{\psi}$ (Q) ln [P$^{\psi}$ (Q) / P$^{\psi}$ข (Q)]   (15)

Q ฮ {N,B,S}

Table 10b : Speed of Adjustment Comparison when a short sale is allowed. (i.e. $h_l=h_U=1$). One can calculate the speed of adjustment by using the mean values of the estimates parameter from Table 9a in equation (15). Average γ Values are in Parenthesis.

Portfolio	5 Min	10 Min	15 Min
For First Decile			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.1100	0.0665	0.0314
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.0202	0.0219	0.0142
Average γ Values	(0.7192)	(0.6476)	(0.6040)
For Fifth Decile			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.3377	0.2919	0.1299
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.0036	0.0097	0.0041
Average γ Values	(0.9325)	(0.8763)	(0.8707)
For high volume SET-50 portfolios			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.0751	0.0721	0.0438
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.0154	0.0336	0.0244
Average γ Values	(0.7035)	(0.6036)	(0.5784)
For low volume SET-50 portfolios			
Convergence rate of 'Good' News, $I_P^H(P^O)$	0.1468	0.1049	0.0422
Convergence rate of 'Bad' News, $I_P^L(P^O)$	0.0076	0.0164	0.0108
Average γ Values	(0.8384)	(0.7358)	(0.6753)

Note: $$I_P\psi(P\psi\text{ข}) = \sum_{Q \in \{N,B,S\}} P^{\psi}(Q)\ \ln\left[P^{\psi}(Q) / P^{\psi\text{ข}}(Q) \right] \qquad (15)$$

Table 11 : Summary of the joint probability that the informed insider can exploit from his private knowledge of future value of the stock. One can calculate the probabilities by using the mean values of the estimated parameters from Table 9a in equation (16)

Portfolio	5 Min	10 Min	15 Min
For the volume decile.			
π_I for first decile	0.1261	0.1019	0.0674
π_I for fifth decile	0.0478	0.0414	0.0566
For the SET-50 portfolios.			
π_I for high volume.	0.1066	0.1236	0.0937
π_I for low volume.	0.1298	0.0879	0.0508

Note: $\pi_I = \alpha\delta\mu h_I + \alpha(1-\delta)\mu$ (16)

Table 12 : Summary of the joint probability that the informed insider can exploit from his private knowledge of future value of the stock. One can calculate the probabilities by using the mean values of the estimated parameters from Table 9a in equation (17)

Portfolio	5 Min	10 Min	15 Min
For the volume decile.			
π_U for first decile	0.4460	0.6049	0.6770
π_U for fifth decile	0.1211	0.5670	0.2430
For the SET-50 portfolios.			
π_U for high volume	0.4900	0.6269	0.7029
π_U for low volume	0.3059	0.4776	0.5912

Note: $\pi_U = (1 - \alpha\mu) [1 - \gamma(1-h_U)]$ (17)

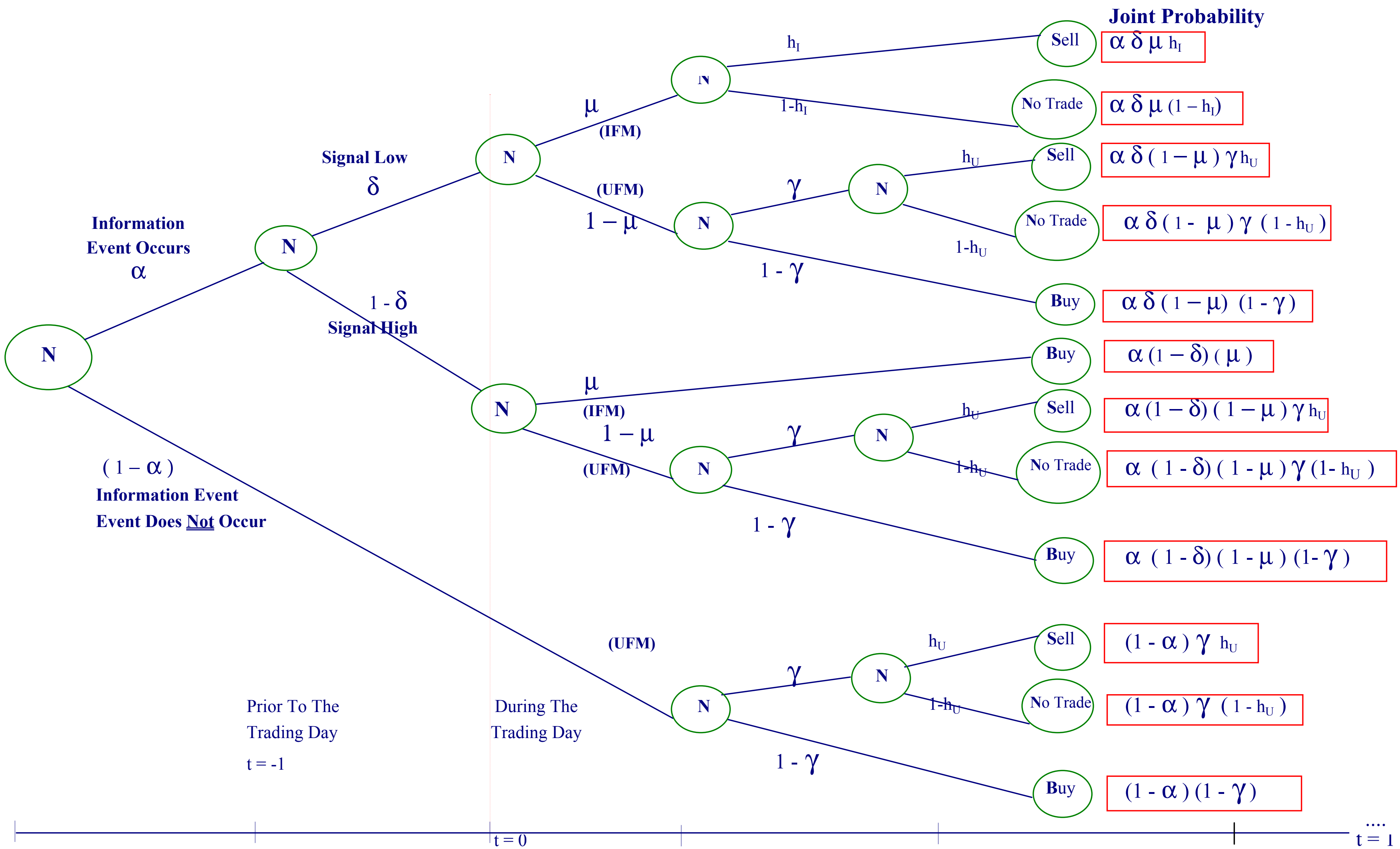

Figure 1 : Tree Diagram of The Trading Process

N = Nature, IFM = Informed insider trader, UFM_L = Uninformed liquidity trader

α = The probability that an information event occurance

δ = The probability of a low signal

Nodes to the left of the dotted line occur only at the beginning of the day

μ = The Probability that trader comes from an informed trader.

γ = The probability that an uninformed trader wants to be a seller

h_I = Probability that a IFM trader already owns the stock

h_U = Probability that a UFM trader already owns the stock

Nodes to the right are possible at each trading interval