Market Microstructure: What can we learn from ultra-high frequency data on the Stock Exchange of Thailand?

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In this article, we discuss the value of studying intraday trading data by providing economic background in the area of market microstructure. We highlight the use of ultra-high frequency data in the study of market design and quality as well as asset pricing. To illustrate, we review recent research papers that utilize the Stock Exchange of Thailand's intraday trading data and explore future research opportunities in this area in order to evaluate market policies and enrich our understanding of the price discovery process on the Thai exchange.

Introduction

Intraday data, once highly guarded by exchanges, has become more readily available to the public over the years. Apparently, it is not the ever growing power of the desk top PC to process large scale datasets alone that has driven a growing body of research utilizing ultra-high frequency data. Rather, it is the need for regulators to evaluate market mechanics that best respond to investors requirements and the need for academics to better understand the relationships among market participants, trading costs, and trading process in their quest for an alternative asset pricing paradigm.

Market microstructure deals with the trading of financial assets and the evolution of asset prices by taking into account of transaction costs, incomplete information, and heterogeneous expectations. The study of market microstructure requires transaction level data (intraday) that allows examination of short run price behavior that can lead to systematic mispricing in the long-term. It allows assessment of the impact of trading mechanisms,

for example, tick rules, trading halts, and upper and lower price bounds, on market quality, which means transparency and accurate price discovery.

The purpose of this article is to provide readers with basic economic background on market microstructure. It is not a complete review of all issues in market microstructure[1] as we are admittedly biased towards topics which relates to the structure of limit order markets and to recent research papers on the microstructure of the Thai equity market. In the next part of the paper, we discuss the role of equity markets, market types and trading protocol to familiarize readers with the institutional set up of organized exchanges. In section 2, we describe two basic modeling issues in market microstructure, which are the price discovery process and theory of bid-ask spreads. Section 3 and 4 provide discussion on market design, asset pricing, and review related literature in the area, particularly those utilizing the Stock Exchange of Thailand's intraday data. Section 5 concludes the paper and propose directions for future research on the microstructure of Thai capital markets.

1. Market Types and Trading Protocol

1.1 Order driven vs Quote driven markets

There are two types of trading systems; a quote driven market and an order driven market. In a quote driven market, buyers and sellers submit their bid and ask offers to designated market makers, also known as dealers or specialists. Based on information in their order books, the market makers will post bid ask prices. Therefore, a quote driven market only displays the bid and ask offers of designated market makers. After individual orders are submitted,

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[1] See O'Hara (1995), Madhavan (2000) and Stoll (2003) for very comprehensive reviews. Also see special issue of International Review of Financial Analysis Vol. 15, 2006 on Asian market microstructure.

the market maker will either fill in customer orders from its own inventory or match the orders with another order. Quote driven trading is used in the major US exchanges, i.e. NYSE, AMEX, and NASDAQ and on the London Stock Exchange (LSE).

Unlike quote driven markets, order driven markets, operate without the intermediation of market makers. Instead, buyers and sellers submit the prices and quantity which they are willing to buy or sell a security. These buy and sell orders are displayed and accumulated in a limit-order book and order execution is usually prioritized based on price and time. A majority of exchanges around the world adopt order driven systems and utilize computerized order matching. In some markets such as NASDAQ, a hybrid system, employing both dealer intermediation and direct crossing of individual orders, is used.[2] The use of hybrid systems allows participants to enjoy the transparency of limit order book disclosure and the adequate provision of liquidity for illiquid assets.

1.2 The trading process on the SET

Trading on the Stock Exchange of Thailand (SET) is predominantly based on an order driven system. The process begins when the buyer or seller submits their orders via the brokerages. These orders are then electronically submitted from the brokerages to the SET's computerized order matching system which automatically queues orders and matches them according to a single price that generates the greatest trading volume at opening and close and according to price-then-time priority during opening hours. Alternatively, orders can be submitted by a "put-through" system which allows brokers to deal directly with each other for their own

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[2] To trade a stock listed on the NASDAQ, the broker can send the order to a market maker, an order-matching facility called an alternative trading system (ATS), or an electronic communications network (ECN).

trades or on behalf of their clients.

To curb excessive volatility, the SET imposes a 30% band on daily price fluctuations relative to the previous day closing. A circuit breaker is implemented if the market index falls by 10% from the previous days' close. There is also a minimum price increment requirement for stock quotations. The current tick rule in use is summarized in the following table.

Group	Lower (From Bt)	Upper (to less than Bt)	Tick Size (Bt)
I	<2	-	0.01
II	2	5	0.02
III	5	10	0.05
IV	10	25	0.1
V	25	50	0.25
VI	50	100	0.5
VII	100	200	1
VIII	200	400	2
IX	400	800	4
X	800	-	6

2. Modeling Issues

2.1 The price discovery process

Price discovery[3] is the process of finding the market's consensus or equilibrium value of a share. More specifically, what we demand from an organized exchange is that it provides an environment to ensure efficient price discovery, which means that consensus prices where trading occurs reflect assets' true valuations. Hence, the concepts of price discovery and market efficiency are very

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[3] See Journal of Financial Markets, 5, 2002 for special issue on price discovery.

much tied, the latter describes the arrival speed of market consensus or equilibrium price. There are two main reasons why observed asset prices generally depart from their underlying efficient values. First, is the existence of market frictions, which includes explicit (commission costs and taxes) and implicit costs of trading (i.e. bid-ask spreads, thin limit order book, and price impact). Second, is the limitation of investors to process information sets with precision.

2.1.1 Random information but not so random prices

An efficient market, put simply, is a market where securities incorporate new (accurate and timely) information quickly into their prices. It can also be described as a market where the price of a security at any given time t reflects information set Ω_t available up to that point and thus the best forecast of future security value is the last price observed. This implies that future price variations are unpredictable since information arrival is unpredictable. The well-known random walk model of asset prices can be expressed as,

$$p_t = p_{t-1} + \varepsilon_t$$

where p_t is today's price and p_{t-1} is yesterday's price, and the random error term, ε_t represents unexpected and unpredictable arrival of new information. Alternatively, we can rewrite the above representation that the daily change in price levels or rate of return, r_t is driven by the random error term as in,

$$r_t = \Delta p_t = \varepsilon_t$$

But if we assume that information is random, then why do we empirically observe price trends and return predictability? Consider the fund manager of One Asset wishing to buy 350,000 shares of PTTEP can try to buy all shares at once at the likelihood of a substantial premium. Thus, he is likely to split his buys into small orders to reduce market price impact. The splitting of large

orders is one reason among others that leads to persistence in order flows and continued price trends. To examine this problem more formally, suppose investors receive public information set Ω_{t-1} at time $t-1$ and decide to trade on that information in the subsequent period, the expected quantity of trade is defined as $E_{t-1}[x_t|\Omega_{t-1}]$. Now suppose the actual trade quantity at period is xt, then the difference $x_t - E_{t-1}[x_t|\Omega_{t-1}]$ should reflect trade innovation in response to unanticipated news during that trade period. Therefore, one simple way to measure how fast the stock responds to new information is to estimate the size of intraday quote revisions in response to order flows.

Table 1 provides a comparison of quote revisions between a highly visible and highly liquid stock, Siam Cement (SCC) and a less visible and less liquid stock, Lanna Lignite, (LANNA). In a simple bivariate model between average percentage quote revisions, r_t and signed order volume[4] in thousands of shares, x_t at each half hour time interval shown in the model below,

$$r_t = c_0 x_t + c_1 x_{t-1} + c_2 x_{t-2} + c_3 x_{t-3} + u_t \qquad (1)$$
$$x_t = d_1 x_{t-1} + d_2 x_{t-2} + d_3 x_{t-3} + w_t$$

Table 1 reports the impact of signed trade on SCC and LANNA over three lagged half hour time interval using 2003 data. Since we view the signed trade volume as trade innovations to new information, the cumulative quote revisions can be interpreted as information revealed in the trade. In sum, Table 1 shows the impact of trade innovation on SCC value is stronger particularly at the contemporaneous level where a 1,000 share trade increases quote revision in the same direction by 0.4%. By the third half hour after the trade, the cumulative quote revision is down to 0.2%. On the other

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[4] The signed trade volume receives a positive (negative) value if it is buyer (seller) initiated.

hand, LANNA's quote revisions appears less related to the direction of trade innovations.

2.1.2 Common value auctions and dynamic learning

Limit order markets function like an auction system where the buyer with the highest bid and seller with lowest asking price wins the deal. An investor's order submission price depends on the bidder's perception of the asset value. In general, the value of assets can depend on independent private values where other people's bids and offers have no influence on a person's valuation. For example, at an art auction, an investor's acquired taste for, let's say, an Aboriginal painting determines his private valuation and the maximum price he is willing to pay to acquire the art piece. Other people's bid prices for the same art piece at the auction do not impact his private valuation. In contrast, affiliated values are personal valuations that are positively related to the private values of other bidders. The hype for internet stocks in the US in the late 1990s and for Thai energy stocks during the oil price run-up in recent years are good examples. The third type of valuation is common values which are intrinsic values that are unknown to investors but will be the same across all bidders. For example, the exploration rights for oil and gas in the gulf of Thailand.

In securities markets, investors' valuations of stocks are generally dominated by common components whereas both independent private values (i.e. personal preference, such as, investment horizons, risk aversion, and tax situations, and affiliated private values (i.e. herding behavior and momentum trading) have weaker influence. This is because the market consists of a large number of investors and there is large probability of resale. The only problem with finding common values in practice is that investors will receive different signals or information of what the securities are worth. Thus, learning from past price and trading volume is part of the process to price discovery.

Consider a market with four investors, indexed $i = 1,..,4.$

Each investor i receives different signal, s_i which is random valuation between 0 and 40 for a security. Let the true common value of the security be the average of the signals, $V = \Sigma_{i=1}^{4} s_i / 4$. Knowing only the possible range of the valuations but not the signal, the estimated value of V or expected value of the security $E(V) = 20$. Suppose investor 1 receives $s_i = 30$, then $E(V | s_1 = 30) = (30 + 20 + 20 + 20)/4 = 22.50$. Now let's say this investor bid Bt 22.50 and wins the auction, it must be that he is the investor with the highest signal. He should then adjust his bidding strategy accordingly such that, $E(V | s1 =30$ and s2, s3, s4 <30$)$. Conditional on the new information that the average signal must be lower than 30 or E $(s|s<30)=15$, the first investor adjusts his expectations down such that $E(V | s1 =30$ and $s_2, s_3, s_4 <30) = (30+15+15+15)/4=18.75$. Although this example oversimplifies the process of dynamic learning, it illustrates that past prices can provide valuable information about common values. As a matter of fact, when we see execution price for any stock rising and at heavy trading volume and open interest, we tend to raise our expectations of security values.

There exists a number of models that explain the dynamic learning process. Earlier models based on dealership market can be found in the important work of Glosten and Milgrom (1985) and Kyle (1985). These two models provide a framework of how a market maker learns about the intrinsic value of a security over time by trading with informed traders in a sequential and continuous trading model, respectively. Thus, the focus of such models is on Bayesian learning and the risk of trading with informed traders. In a limit order structure, like the SET, the problem of trading with better informed investors still holds.[5] At the same time, there are

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[5] In their comparative study of Singapore and Thai market, Bailey, Mao, and Sirodom (2007) show that foreign investors have better information processing than local investors in the Thai market. Moreover, Bailey et al. (2006), find that both foreign and local investors who trade cross-market possess superior information.

two additional complications, the risk that a limit order fails to fill (execution risk) and the risk that the order takes time to fill (picking-off risk). The latter can cause unexpected loss since the investor fails to monitor his limit order and revise his order when there is a change in security valuation.

A recent model developed in Hollifield, Miller, and Sandas (2004) illustrates the order submission process of a trader in a limit order market. In the model, a risk neutral trader values an asset worth v_t, which is comprised of a common value, y_t and private value, u_t

$$v_t = y_t + u_t \qquad (2)$$

The common value changes as the investor learns new information, δ_t, which satisfies, $E_{t-1}(\delta_t) = 0$ with ,

$$\Delta y_t = \delta_t \qquad (3)$$

Suppose a trader with valuation $v_t = y_t + u_t$ submits a buy order quantity of q_t at a price $P_{t,b}^{BUY}$, b ticks below the current best ask quote. Let indicator $d_{t,b}^{BUY} \in [0,1]$ denote the trader's order submission, where $d_{t,b}^{BUY} = 1$ if the trader submits a buy limit order at the price b ticks below the current best ask quote. Define $Q_{t,T}$ as the total number of shares actually filled when the order was submitted at time t and cancelled at time T. Then let the execution probability of a buy submission at time t, ψ_t^{BUY} be equal to,

$$\psi_t^{BUY} = E_t [Q_{t,T}/q_t \mid d_{t,b}^{BUY} = 1, q_t] \qquad (4)$$

Note that the term $Q_{t,T}/q_t$, is the proportion of total order quantity filled. The picking-off risk is defined as,

$$\xi_t^{BUY} = E_t [Q_{t,T}/q_t (y_T - y_t) \mid d_{t,b}^{BUY} = 1, q_t] \qquad (5)$$

Here the term, $(Q_{t,T}/q_t)(y_T - y)$ captures potential profit or loss from change in common values over the period $T-t$ during which the trader fails to monitor his limit order and update new information that affects the security's common value. The trader's expected pay-off conditional on his information set is then,

$$E_t[(U_{t,T}) \mid d_{t,b}^{BUY} = 1, q_t, u_t] = q_t \, \psi_t^{BUY}(V_t - P_{t,b}^{BUY}) + q_t \, \xi_t^{BUY} - q_t c \quad (6)$$

From equation 6) if on average, the entire order is filled and common values moves favorably during the execution period, the trader earns a positive pay-off worth the submitted order quantity times excess value on immediate execution plus the order quantity times the positive change in common values minus the trading cost, which is order quantity times commissions rate, c. In contrast, the trader can also earn a loss if common values move out of his favor. The key to ensuring positive expected payoff depends on the accuracy of the bidder's private information and how this relates to future change in common values. The higher the private signal, the more aggressive is the bid and hence, the higher the probability of execution and the expected pay-off.

2.2 The Theory of Bid-Ask Spreads

Investors usually frame market frictions only in the context of explicit trading costs, which are commissions and taxes. In reality, market frictions consist of implicit costs in microstructure. These include bid-ask spreads, thin limit order book, tick size, and price impact. We discuss here first the role of bid-ask spreads. By definition the bid-ask spread is the difference between ask and bid price. Since the SET displays the best (highest) three bids and best (lowest) offers available to the public, we typically refer to the inside spread as the difference between the most aggressive bid and ask as shown in the box below.

Ask3	Ask2	Ask1	Bid1	Bid2	Bid3
102	100	99	98	97	95

Inside spread

When submitting an order, the size of the spread tells us the price of immediacy. Consider stock A with best bid at Bt 200, best offer at Bt 212, and thus a spread of Bt 12. An investor whose private assessment of stock A is Bt 206 and requires immediacy will have to buy stock A at Bt 212 which is Bt 6 above his private valuation or sell stock A at Bt 200 or Bt 6 below his private valuation. On the other hand, if stock A's best bid and offer had been Bt 204 and Bt 208, respectively, his cost of immediacy would only have been Bt 2.

2.2.1 The determinants of bid-ask spreads

There are various reasons why bid-ask spreads exist. First, is explicit trading costs (commissions and taxes). From an economic perspective, an investor with private valuation of stock i worth v_i will submit a bid price b_i such that $v_i - b_i \geq 0$. In a market with no other frictions, b_i should only be a function of private value v_i and fixed rate commissions, ψ, hence $b_i(v_i, \psi)$. For instance, an investor's private valuation of a stock is Bt 100. Let commissions be 0.5% of transaction value. The investor's maximum bidding price will be Bt 99.50 (100 - (100*0.005)). By symmetry, if the investor is a seller, his optimal order submission strategy will be such that $a_i - v_i \geq 0$. Therefore, his minimum's asking price will be Bt 100.50 (100 + (100*0.005)). Unless private valuations change, the switch between buying and selling activity will cause observed trading prices to swing between Bt 99.50 and Bt 100.50. In microstructure literature, this is known as the bid-ask bounce.

The second determinant of bid-ask spreads is the degree of information asymmetry otherwise known as the adverse selection problem. Markets typically consists of traders with different

information accuracy. Since some investors have better information than others and it is not possible to tell whether we are trading with an informed or uninformed counterparty, bid-ask prices are set to account for this risk. A simple way to think about this is when we consider buying a used car. Suppose a used 2005 Toyota in perfect condition is worth Bt 750,000. However, we are likely to put some discount to this price to accommodate undisclosed downside qualities of the car when dealing with an unknown seller. Likewise, in the trading of financial assets, such as equity, bidders place orders at discount of their private values whereas sellers place offers at premium of their private values. By taking adverse selection costs into account, the investor's bid function now becomes, b_i (v_i, ψ, ξ_i), where ξ_i represents the adverse selection discount for the stock. Figure 1 provides an illustration of the components of total spread.[6] The figure shows that the size of the spread depends on commissions as well as adverse selection. While it is straightforward to determine the size of ψ, the size of ξ_i can only be inferred from empirical data. Such inferences are possible using various modeling techniques discussed in the following section.

At this stage it is useful to discuss the intuition behind the size of ξ_i. The adverse selection premium or discount depends on how much investors know about the stock in general. Larger firms that receive more visibility from more analyst and news coverage tend to have lower asymmetric information problem, and thus lower percentage bid ask spreads, ceteris paribus. In addition, firms with larger price volatility, tend to have larger spreads.[7] This is because volatility reflects uncertainty about values. In Figure 2, we show the

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[6] Unlike dealership markets usually modeled in the US, the spread in a continuous double auction market such as the SET, need not be symmetric. The symmetry in spread setting of dealership market is justified in Glosten and Milgrom (1985) famous sequential trade model.

[7] See Visaltanachoti, forthcoming International Review of Financial Analysis for evidence on the SET.

percentage bid-ask spreads[8] of SET50 and non-SET50 groups by month during the year 2003. The bar charts reveals a consistent trend that the percentage spreads for non-SET50 stocks are about twice as high as the SET50 group.

2.2.2 Decomposing the bid-ask spreads

Theoretical work on the compositions of bid-ask spread is extensive. Although these models are originally written for dealership markets, it is possible to treat limit-order traders as their own market makers. In general these models show that the change in price come from two main sources, adverse selection costs denoted by variable α and order processing costs, β as shown in equation (7). The intuition behind this model is that in absence of new information, the price of a security changes because transaction occurs either at the standing bid, where trade indicator variable, I_t takes the value $+1$ or at the standing ask, where I_t takes the value -1. Suppose a stock has a standing best bid at Bt 100 and standing best ask at Bt 102. Without new information, the price swings between Bt 100 and Bt 102, depending on whether it is buyer-initiated or seller-initiated. Such swings are also referred to as the bid-ask bounce where the spread of Bt 1.0 accounts for order processing cost, β which is predominantly determined by the minimum price variation rule, or tick size. The other determinant of security price change comes from information in the last trade measured by the term $\alpha q_t I_t$, which is usually referred to as the price impact, where qt is the number of traded shares. A large value of the price impact term is associated with high adverse selection cost since large movements in prices from new information reflects the degree of market "surprise" that has not been incorporated in earlier price.

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[8] Quoted spread divided by the mid-point, where quoted spread is defined the difference between the best bid-ask spread and the mid-point is defined as (bid+ ask)/2.

$$\Delta p_t = \alpha q_t I_i + \beta (I_t - I_{t-1}) + \varepsilon_t \qquad (7)$$

For the purpose of application on the SET, we choose to elaborate on two stylized models. In the first model introduced in Huang and Stoll (1997), we make some adjustments to the original work to accommodate for the limit order structure and clientele composition on the SET by ignoring inventory costs. Instead, we include indicator variables for intra (within) main board trades and cross-market trades (trades crossing from foreign board to local board). We disregard inventory costs since limit order traders do not maintain stock inventory positions like dealers. The motivation to include the indicator variables for intra main board trades (Q_t^M) and cross-board trades (Q_t^C) is due to Bailey, Mao, and Sirodom (2006). The authors find evidence that investors who cross the foreign board to trade on the main board have superior information. Let the unobservable fundamental value of the stock v_t in absence of transaction costs be,

$$v_t = v_{t-1} + \alpha(S/2)Q_{t-1} + \varepsilon_t \qquad (8)$$

where S is the constant spread, α is the percentage of the half spread due to a consequence of adverse selection, Q_t is the buy-sell trade indicator variable, and ε_t is the serially uncorrelated public information shock. Now if trades can be classified as intra main board trades and cross board trades, it is possible to rewrite the above equation as,

$$v_t = v_{t-1} + \alpha^M(S^M/2)Q_{t-1}^M + \alpha^C(S^C/2)Q_{t-1}^C + \varepsilon_t \qquad (9)$$

Q_{t-1}^M = trade indicator variable for intra main board trades, taking the value of +1/-1 if the trade is buyer (seller) initiated.

= 0 otherwise

Q_{t-1}^C = trade indicator variable for cross board trades, taking the value of +1/-1 if the trade is buyer (seller) initiated.

= 0 otherwise

S^M = spread from intra main board trades

S^C = spread from cross-board trades

The adjusted equation allows values of adverse selection α's to differ. More explicitly, α^M is the proportion of the spread of intra main board trades from adverse selection, and α^C is the proportion of the spread of cross-board trades from adverse selection. The empirical result from Bailey, Mao, and Sirodom (2006) suggests that $\alpha^C > \alpha^M$ as cross-board trades have superior information, and hence, they are expected to have larger proportion of spread from adverse selection. We can also show that the security price, p_t is determined by its fundamental value v_t, its implicit trading costs or spreads and error term, η_t such that,

$$p_t = v_t + (S^M/2)Q_t^M + (S^C/2)Q_t^C + \eta_t \qquad (10)$$

Combining equations 9) and 10) yields the expression,

$$\Delta p_t = \alpha^M (S^M/2)Q_{t-1}^M + \alpha^C(S^C/2)Q_{t-1}^C + (S^M/2)(Q_t^M - Q_{t-1}^M)$$
$$+ (S^C/2)(Q_t^C - Q_{t-1}^C) + \varepsilon_t + \Delta\eta_t \qquad (11)$$

The first two terms in equation (11) captures the information effect from adverse selection. The larger the value of α's implies a larger amount of asymmetric information revealed by the trade. The 3rd and 4th terms measure the bid-ask bounce. Rearranging equation (10) yields,

$$\Delta p_t = (S^M/2)Q_t^M + (\alpha^M - 1)(S^M/2)Q_{t-1}^M + (S^C/2)Q_t^C$$
$$+ (\alpha^C - 1)(S^C/2)Q_{t-1}^C + e_t \qquad (12)$$

An alternative bid-ask spread decomposition model is the

general framework of Madhavan, Richardson, and Roomans (1997)[9] as shown next,

$$\Delta p_t = \alpha(Q_t + \rho Q_{t-1}) + \beta(Q_t - Q_{t-1}) + u_t \qquad (13)$$

where α measures private information impact, β measures transaction costs and ρ measures the autocorrelation in trades. Again, the first term captures the information effect and the second captures the bid-ask bounce. While estimation of adverse selection and transitory order processing costs from these models appear straightforward, it requires very active intraday trading data to reduce estimation error from stale limit order books. Hence, application on the SET is likely to be limited to stocks in the SET 50.

3. Market Design: The role of price limits and tick size

Exchanges have an unquestionable goal of promoting market quality. In the ensuing 32 years of the Thai bourse,[10] the market regulators have introduced a number of changes to improve liquidity and price discovery as well as reduce trading costs. To ensure that these goals are met, the SET imposes a number of mechanisms, among them include, daily price limits and tick size rules. These mechanisms are commonly found in other exchanges around the world although each market has varying degree of restrictions. For example, the London Stock Exchange imposes trading halts if stocks in certain price range experience 25% price movement from last trade whereas the price limit on the Korean

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[9] This model is used in Ahn, Hamao, and Ho (2002) to decompose bid-ask spread of the Tokyo Stock Exchange, which is also a limit-order market like the SET.
[10] The SET was formally established in 1975, but before then organized trading was done on the Bangkok Stock Exchange.

Stock Exchange is limited to only 15% with respect to previous day's close. Tick size, or the minimum price variation allowance for stock quotations also differs from market to market. The American Stock Exchange (AMEX) abandoned tick size rules and introduced decimalization in 2001. The German Deutsche Bourse also adopts decimalization. Elsewhere in the world regulators use a uniform tick size regardless of stock price (i.e. pre - 1997 AMEX tick size is $1/8) or a tick size schedule that is a step function of stock price (i.e. Bangkok, Paris, Stockholm, Toronto, and Tokyo). We provide here some discussion of existing studies on price limits and tick size and recent findings on the issue with policy implications for the SET.

Volatility is a double-edged sword. Too much of it leads to market instability, but without it, we could be looking at a market that fails to respond to information. Whether markets need to be protected with price limits remains an open question as studies on the effectiveness of price limits is scarce. Chen (1998) and Kim and Rhee (1997) document price continuations following price limit hits suggesting that the limits are restricting price to adjust to its fair value. Kim and Limphapayom (2000) use daily and monthly data from the Taiwanese Stock Exchange and the SET to examine the characteristics of stocks that frequently hit price limits. They find that small, actively traded, and volatile stocks tend to hit price limits more often. In particular, they note that actively traded stocks which carry more information flow hit price limit frequently is further evidence that these price limits could potentially be obstructing faster price adjustment. The work of Kim and Limphapayom (2000) can be extended by exploring whether the same characteristics hold for stocks with high intraday volatility.

Turning to the issue of tick size, a few recent papers, Pavabutr and Prangwattananon (2007), henceforth PP (2007) and Boonvorachote, Charoenwong, and Sirodom (2006a, 2006b), hence forth BCS (2006a, 2006b) examine the impact of tick size change on transaction costs and liquidity. The study on tick size merits

analysis because its existence has both benefits and costs.[11]

On one hand, it creates additional transaction costs for traders on top of commission fees. Suppose a stock has intrinsic value of Bt 100. Taking into account of commission fees, the ask price that clears the fee should be Bt 100.50. However, since the minimum price variation for stocks between Bt 100 - Bt 200 is Bt 1.0, the asking price must be set higher at Bt 101. This new price reflects an additional Bt 0.50 of discreteness related cost that a market order buyer must pay. On the positive side, minimum price variations discourage front-running and reduce bid-ask spreads (Harris (1994), Goldstein and Kavajecz (2000), Lau and McInish (1995), Niemeyer and Sandas (1994)).

PP (2007) evaluates the impact of exogenous change in tick size. The SET reduced minimum price variations for stocks priced below Bt 25 on November 25, 2001. The paper finds that tick reduction is associated with a decline in spreads, and in quoted and accumulated market depths. However, using relative comparisons to a control group, it appears that tick reduction is only successful in increasing volume of stocks in the range from Bt 10 to less than Bt 25, but not for those trading below Bt 10. BCS (2006 a, b) questions the effectiveness of the SET's multiple tick size regime by examining endogenous changes in tick size on transaction costs as well as the order submission strategy. Their findings support PP (2007) that small ticks are more effective in improving market liquidity. However, since their study includes stocks in all tick ranges, they also find evidence that endogenous tick reduction in stocks in the high price range of Bt 200 - Bt 400 or those with tick size above Bt 1 also leads to substantial reductions in bid ask

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[11] Angel (1997) and Anshuman and Kalay (2002) provide an economic model for optimal tick size. The models share the conclusion that the optimal tick must minimize trading costs. In Angel (1997), the optimal tick size is increasing in firms' market values and idiosyncractic risks. In Anshuman and Kalay (2002) the optimal tick depends on the trade-off between adverse selection and the price discreteness.

spreads. At the same time, they show that tick size above Bt 1 enlarges the proportion of limit order submission, which tends to result in higher transaction costs for market order traders. In combination, these findings suggest that the SET applies a uniform tick size of Bt 1 for stocks above Bt 100 to reduce transaction costs of stocks in the high price range.

4. Asset pricing: A closer look at "Liquidity"

Asset pricing has many dimensions. With parsimony in mind, asset pricing can be viewed as three dimensional consisting of risk, return, and liquidity. While we find the concepts of risk and return unambiguous to describe, liquidity is actually a broader and more elusive concept than the familiar trading volume, trading value, and turnover. This is because liquidity encompasses a number of transactional properties of markets (see Kyle (1985)). These include tightness (the cost of turning around a position over a short period of time), depth (the size an order flow innovation required to change prices), and resiliency (the speed which prices recover from a random, uninformative shock). Table 2, provides a list of possible measures of liquidity. These liquidity proxies are all correlated to each other so that it is difficult to pin-point what aspect of liquidity each of them captures. Panel A of Table 3 reports the average selected daily and intraday liquidity information of SET50 and non-SET 50 stocks for the period 2003. The numbers clearly show that SET50 stocks are more liquid than non-SET50 by both intraday and daily measures. While it is not surprising that SET50's trading value and volume is substantially greater, the smaller percentage bid-ask spreads and intraday price impact, λ quantify the implicit trading costs. Panel B of Table 3 summarizes the correlation among these liquidity variables and firm market capitalization. As shown, there is clearly a negative relationship between market capitalization and measures of trade friction i.e. bid-ask spreads and intraday price impact. This finding reminisces the work of Chaiyachantana et al.,

which uses institutional trading data of 37 countries to analyze c ross-country differences in price impact. They find that price impact is an important composition of transaction costs and that it is negatively correlated to firm size and positively correlated to the size of the order.

Researchers include liquidity risk as part of equity pricing. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Amihud (2002)) finds that firms' liquidity characteristics determine cross-sectional return variation. More specifically, expected return is decreasing in liquidity. This means investors require compensation for holding illiquid stocks. Chordia, Roll, and Subrahmanyam (2000) Huberman and Halka (2001) document strong liquidity commonality suggesting that liquidity risk is systematic.

Notwithstanding the abundance of literature on liquidity on US markets, evidence on the role of liquidity on the Thai Exchange is quite limited. On the Thai exchange, Visalthanachoti et al. (2006) examines the liquidity distribution or the shape of the limit order book and its determinants. They find that the convexity in the shape of the order book[12] is related to firm size. Their finding is indicative that small firms with high return volatility are likely to be more sensitive to adverse selection problems. Gorkittisunthorn et al. (2006) extends this result by examining how bid-ask spreads change following stock split events. They find that stocks with high insider ownership do not exhibit significant improvement in bid-ask spreads, consistent with the conjecture that the risk of adverse selection is negatively related to liquidity. These findings are indication that we would

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[12] The shape of the limit order book refers to the outstanding submitted order quantities at various prices. Convexity and concavity in the shape of limit order book refers to the change in slope of the order book. The slope itself, measures the change in the ratio between adjacent spreads to adjacent quoted depths (order quantities). The convexity (concavity) of the order book is associated with higher (lower) liquidity and lower (higher) spreads at the best quotes.

expect firm size and their liquidity characteristics should be related to their required returns.

Pavabutr and Sirodom (2007) also use split events in their study. However, their focus is more specific on evaluating the impact of stock splits trading activities and trading costs. They argue that existing empirical finding on stock split impact on liquidity is ambiguous because liquidity needs to be assessed from different aspects. Thus, the study provides analysis of pre- and post-split changes in trading activities and price impact measures of trades. The study finds successful splits, which are the ones that reduce price impact and raise adjusted stock price, tend to be those that bring stock prices down to investors' preferred trading range of Bt 25 - 50. This finding combined with PP (2007) suggests that the clustering of stock trading around this price range could be a result of it creating a balance between reducing the cost of discreteness while at the same time preserving a reasonable margin for trading profits.

5. Conclusion

The SET has recently made intraday data available to academic research. The quality and the nature of intraday data disclosure allow a number of interesting research agendas. On issues of market design, further study on the optimal trading price range and optimal tick size can provide us better understanding in our search for optimal price variation rules that minimizes trading costs and ensure orderly trading. To our knowledge, there is no existing research that evaluates the effectiveness of SET's use of daily price limit of 30%. The daily price limit is non-existing in some markets whereas others impose an even tighter daily price variation than the SET.

On issues of asset pricing, the role of liquidity, their intraday proxies, and their relationship between price discovery can be assessed in greater detail. In particular, a number of stocks on the exchange are liquidity-driven given the relatively low free float and

small market capitalization. The disclosure of trader types allows exploration into strategic behavior and traders, their responses to information, and their trade impact on the exchange. We have only just begun. Studies in market microstructure accommodates for the unique characteristics of the Thai market that will surely enrich our understanding of our own market where traditional economic theories fail to explain observed empirical anomalies.
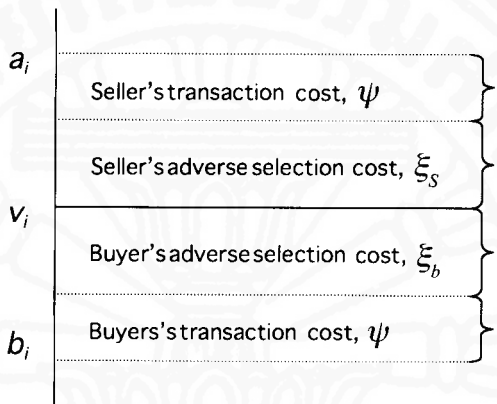
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Figure 1: Components of bid-ask spreads

This figure shows the basic components of the bid-ask spreads around stock i's common private value, v_i. The spread consists of transaction costs, ψ and adverse selection cost, ξ. In reality, the spread need not be symmetric as it is possible for $\xi_b \neq \xi_S$ in a double auction.

a_i	Seller's transaction cost, ψ
	Seller's adverse selection cost, ξ_S
v_i	Buyer's adverse selection cost, ξ_b
b_i	Buyers's transaction cost, ψ

Figure 2: Percentage Bid-ask spreads of SET 50
vs Non SET 50 stocks for 2003

This figure shows the monthly average percentage bid ask spreads by SET50 and non-SET50 groups. The percentage bid-ask spread (%BAS) is computed from Quoted spread divided by the mid-point (bid+ask)/2.

SET50 and Non-SET50 %BAS (2003)
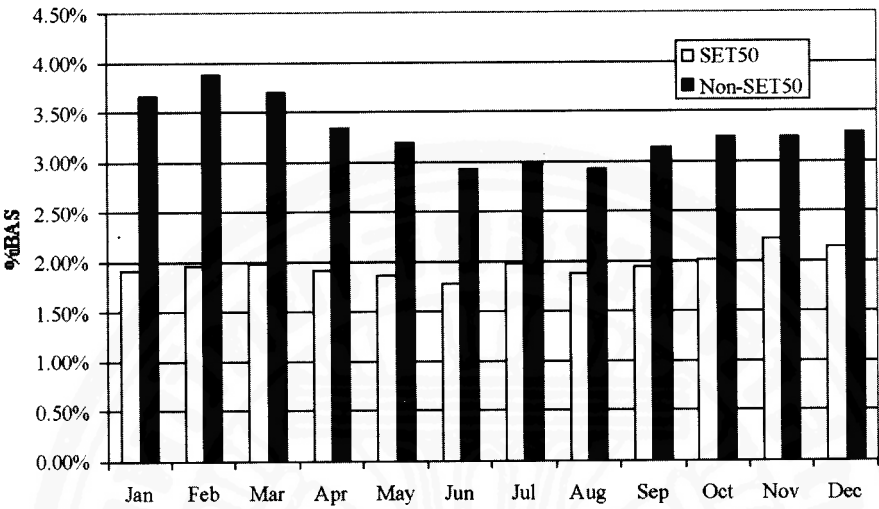
Source: Data source from Stock Exchange of Thailand, spreads computed by authors

Table 1: Intraday Quote Revisions

This table provides the estimates for corresponding the vector autoregressions corresponding to the models

$$r_t = c_0 x_t + c_1 x_{t-1} + c_2 x_{t-2} + c_3 x_{t-3} + u_t$$
$$x_t = d_1 x_{t-1} + d_2 x_{t-2} + d_3 x_{t-3} + w_t$$

where r_t is the average percentage quote revision in each half hour time interval and x_t is the signed trade volume in thousand shares receiving values of positive (negative) for buy (sell) initiated trades. The cumulative quote revision is the sum of c_i through the third time interval. Two stocks are selected, Lanna Lignite (LANNA) and Siam Cement (SCC). Only 2003 data is used.

Time Interval	LANNA			SCC		
	Quote revision	P value	Cumulative Quote rev	Quote revision	P value	Cumulative Quote rev
0	-0.009	0.782	-0.009	0.004	0.000	0.004
1	-0.002	0.961	-0.010	-0.001	0.484	0.003
2	0.002	0.961	-0.009	-0.001	0.360	0.002
3	-0.007	0.827	-0.015	0.000	0.867	0.002

Table 2: Daily and Intraday Measures of Liquidity

This table lists common measures of daily and intraday liquidity. For the daily price impact measure, D_i is the number of trading days in the sample, R_i is stock i return, and $TVAL_i$ trading value of stock i. For intraday price impact measure, q_i is the order flow, D_t is signed trade, which receives value of +1 if it is buyer initiated and -1 if seller initiated. These proxies of liquidity are likely to be related to resilience. Alternatively, we can measure *resilience* by volatility persistence.

Measures	Description	Economic significance
Daily		
Trading volume	Number of shares traded	Trading activity, flow of information, tightness
Trading value	Value of shares traded	Trading activity, flow of information, tightness
Turnover volume	Proportion of shares traded to total number of shares outstanding	Trading activity, flow of information, free float, tightness
Turnover value	Proportion of share value traded to total market capitalization	Trading activity, flow of information, free float
Daily price impact (ILLIQ)	$ILLIQ_i =$ $\frac{1}{D_i} \sum_{i=1}^{D_i} |R_{id}|/Tval_{id}$	Inverse of market depth

Measures	Description	Economic significance
Intraday		
Bid-ask spreads	Difference between ask and bid outstanding (see details in glossary)	Transaction costs, tightness, information asymmetry
Intraday price impact (λ)	$\Delta p_t = \lambda \cdot q_t + \varphi \cdot (D_t - D_{t-1}) + y_t$	Transaction costs, Inverse of market depth
Limit order book depth	Amount of buy and sell order quantities at the inside spread.	Tightness, flow of information, information asymmetry

Table 3: Selected Daily and Intraday Measures of Liquidity (2003 only)

Panel A of this table shows selected average daily and intraday measures of liquidity for SET50 and non-SET50 stocks. Data from 2003 only. Due to missing data or insufficient number of observation in 2003, the number of firms in the SET50 and non-SET 50 is reduced to 38 and 203, respectively. Panel B shows the correlation among the liquidity variables described in Table 2.

Panel A

Variable	SET50 Mean	Non-SET50 Mean	SET50 Median	Non-SET50 Median
Mkt Cap (Bt mn)	41,864	3,531	19,065	1,782
Trade Vol (mn shrs)	7.17	4.37	1.94	0.22
Trade Val (Bt mn)	139	37	62	3
Bid-Ask Spread	0.83	0.55	0.55624	0.26924
% BAS	2.02%	2.86%	1.86%	2.14%
λ	0.0020	0.0029	0.0001	0.0003
No. of firms	38	203	38	203

Panel B

	Mkt Cap	Trade Vol	Trade Val	% BAS	Lambda
Mkt Cap	1.00	0.06	0.54	-0.23	-0.15
Trade Vol		1.00	0.63	-0.15	-0.21
Trade Val			1.00	-0.33	-0.30
% BAS				1.00	0.40
λ					1.00