Essays on trading cost, trade size, and price behavior : empirical evidence from the stock exchange of Thailand

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Essays on Trading Cost, Trade Size, and Price Behavior: Empirical Evidence from the Stock Exchange of Thailand

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ABSTRACT

This dissertation consists of three essays. Essay 1 examines and quantifies various components of the trading costs of stocks listed on the Stock Exchange of Thailand (SET). The sample includes 79 stocks actively traded in 1997. The results show that although traders submitting passive orders gain an immediacy price paid by those using aggressive orders passive traders still face a sizable opportunity cost when their orders are partially filled or totally unfilled. This opportunity cost more than offsets the benefits from the filled portions of the order; therefore, the total trading cost or the implementation shortfall (Perold 1988) of passive limit orders is generally positive. To minimize this implementation shortfall, it is best to submit the order at the prevailing best quote. In addition, the implementation shortfall is positively related to order size, order aggressiveness, and stock price volatility and negatively associated with firm size, stock price, and stock liquidity.

Essay 2 examines the price behavior associated with buy and sell trades of 71 stocks actively traded on the SET from March 2000 to June 2002. During this time, the market experienced three distinct conditions: bullish, bearish, and neutral. The study concludes that the asymmetry of permanent and temporary price impact between buy trades and sell trades is determined primarily by market conditions. Specifically, contrary to the findings in previous studies, the results show that, in bear market conditions, an increase in price induced by a buy trade is mostly temporary, but a decline in price following a sell trade is mainly permanent. Therefore, our results invalidate the proposition that buy trades are more informative than sell trades. However, for very large trades, it appears that, regardless of market conditions, the permanent price impact of buys is always larger than the price impact of sells. This finding is consistent with the hypothesis that buys are better informed

than sells. Finally, the empirical results do not support the hypothesis that a stock's history of price performance explains the buy-sell asymmetry of permanent price impact.

Essay 3 examines trade sizes used by informed traders. The sample includes 73 stocks actively traded on the SET, a pure limit order market, from January 2002 to October 2002, which comprises two distinct market conditions: bull and bear markets. Using intraday data, the study finds that the "medium-to-large" size of trades (i.e., percentile 75 and larger) accounts for disproportionately large impacts on changes in traded and quoted prices. Studies conducted on U.S. markets show that informed traders employ trade sizes that fall between percentile 50 and percentile 95 (Barclay and Warner 1993) and between percentile 40 and percentile 90 (Chakravarty 2001). Therefore, our results support the hypothesis that informed traders on SET (a market where there is no market maker) are able to use larger-sized trades than trades employed by informed traders in the US market where there are market makers who are able to screen out informed trades.

ESSAY 1

AN EMPIRICAL INVESTIGATION OF TRADING COSTS: EVIDENCE FROM THE STOCK EXCHANGE OF THAILAND

1.1 Introduction

This paper analyzes trading costs incurred by market order traders and limit order traders and compares the costs of different order submission strategies, and examines the relationships between trading costs and stock/order characteristics. Previous studies[1] that use transactional data (e.g., Trade and Quote (TAQ) data) focus on trading costs incurred by traders who initiate trades. These studies implicitly assume that trade initiators pay trading costs (e.g., effective half spread) for demanding immediacy, and a liquidity supplier (i.e., limit order trader) gains the effective spread by supplying immediacy.[2] However, limit order traders incur implicit costs that none of those studies take into account. Limit order traders face risks in exchange for the spread gained from supplying liquidity. In particular, unlike market orders, for which execution is guaranteed, limit orders face a non-execution risk (Cohen et al. 1981), which exposes limit order traders to opportunity costs. Opportunity costs may occur when a large portion of a limit order is unfilled, and there is an adverse selection problem associated with unfilled orders. The unfilled portion of a limit order usually needs to be filled later at a worse price than market orders that could have been submitted earlier (Handa and Schwartz 1996; Perold 1988; Wagner and Edwards 1993).[3] Therefore, in order to obtain a better

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[1] See, for example, Bennett and Wei (2006), Berkman et al (2005), Bessembinder (1999, 2003b, 2003c), Bessembinder and Kaufman (1997a, 1997b), Boehmer (2005), Frino and Oetomo (2005), Huang and Stoll (1996, 2001), SEC (2001), and Venkataraman (2001).

[2] Bodurtha and Quin (1990) show that institutional investors can reduce trading costs by trading patiently (e.g., by using more limit orders instead of predominantly using market orders).

[3] In addition, there is an adverse selection problem associated with the filled portions of limit orders, frequently called the winner's curse problem, picked-off risk, or bagging cost (Handa and Schwartz 1996). This problem results from the option character embedded in limit orders (Copeland and Galai 1983). This risk is related to information-based trades initiated by informed market orders against limit orders (or against market makers in quote-driven markets), and it forces liquidity suppliers (e.g., limit order traders and market makers) to demand compensation, which is incorporated into the spread cost (for example,

understanding of limit order trading costs, it is necessary to take the opportunity costs from the unfilled portions of limit orders into account.

To quantify the opportunity cost faced by limit order traders, more detailed data (beyond transactional data, in which only trade and quote are available) are required. Therefore, the present study uses order-level data (not transactional data) to quantify the trading costs incurred by limit order and market order traders. Costs computed from the order-level data are different from costs computed from conventional market microstructure databases (e.g., Trade And Quotes).[4] In the data used in this study, the timing of the order is available, which enables a more accurate characterization of the true cost of trading stocks than would be possible using Trade And Quotes (i.e., TAQ) data, where only reported trade executions are available. That is, information about the time an order was submitted mitigates estimation biases that result from an inappropriate use of benchmark prices.[5] More important, the quantity of stock sought in an order can be considered an ex ante quantity as opposed to the quantity of stock traded, which is an ex post quantity. Specifically, it is possible to evaluate and quantify the two costs of an order using information about an ex ante quantity: that is, the cost of the filled portion as well as the (opportunity) cost of the unfilled portion of an order.

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see sequential trade information-based models by Easley and O'Hara 1987; and Glosten and Milgrom 1985).

[4]These costs are conceptually similar to costs computed by studies using order-level data about institutional equity trades. For example, see the order-level costs reported by Chiyachantana et al. (2004), Conrad et al. (2001) and Keim and Madhavan (1995, 1997) and the trade-package costs presented by Chan and Lakonishok (1995, 1997).

[5]For example, the mid-point at the time an order was submitted is a more appropriate benchmark for measuring the trading cost than the mid-point at the time an order was executed (or the mid-point of the quotes in effect 5 seconds before the trade report time) generally used by researchers using TAQ data. See Bessembinder (2003a) and Peterson and Sirri (2003) for a discussion about methodological issues concerning the relative timing of trades and quotes used when assessing trade execution costs.

The study discussed in this article contributes to the existing literature on trading costs in the following ways. First, most studies that examine trading costs focus on developed markets: for example, NYSE (which has both market makers and public limit orders) and NASDAQ (which is a quote-driven market). Surprisingly, few studies have investigated less-developed markets or pure order-driven markets[6]. The present examination of trading costs for orders on the Stock Exchange of Thailand (a centralized electronic pure order-driven market) is intended to fill this gap. Second, this study uses detailed data, and as a result, it is possible to quantify not only the trading costs incurred by the initiating side of the trade (e.g., price impact cost[7]), but also the costs incurred by the passive side of the trade. In particular, the study empirically quantifies the opportunity cost incurred by passive orders (i.e., limit orders). By adding the price impact cost of the filled portion and the opportunity cost of the unexecuted portion of an order (which results in the well-known implementation shortfall measure[8]), it is possible to examine which types of orders (i.e., market and limit orders) as well as which levels of aggressiveness are optimal (i.e., incur the smallest total trading cost). Finally, this study examines how the price impact cost, opportunity cost, and implementation shortfall relate to a trader's decision variables (e.g., order

[6] Aitken et al. (2004) compare the relative bid-ask spreads of open-outcry versus electronically traded markets. Their empirical evidence, based on three major futures exchanges that transferred trading systems of stock index futures from open-outcry to electronic systems, support the hypothesis that electronic trading can lower trading costs compared to floor-based trading.

[7] Our definition of price impact cost corresponds roughly to effective half spread used by, for example, Bessembinder (2003c), Bessembinder and Kaufman (1997a, 1997b), and Huang and Stoll (1996).

[8]The implementation shortfall measure was developed and popularized by Perold (1988). Specifically, implementation shortfall can be computed as a weighted average of price impact cost and opportunity cost, where the weights are percentage filling rate and unfilling rate, respectively.

aggressiveness and order size) and exogenous factors (e.g., stock market capitalization, stock price volatility, stock price level, and stock liquidity).

The results of the present study show that an aggressive (passive) order incurs a positive (negative) price impact cost for executed orders. In other words, a market order trader who demands immediacy pays a price for it, while a limit order trader who supplies immediacy gains that immediacy price. The results also reveal a sizable opportunity cost for submitting limit orders because the unexecuted portions of limit orders need to be filled at unfavorable prices. The opportunity cost of the unexecuted portions of limit orders outweighs the favorable executed price of the filled portions of limit orders, and as a result, the overall trading cost of a limit order becomes positive (i.e., incurs trading costs). In addition, there is a relationship between stock/order characteristics and the opportunity cost of a limit order. The opportunity cost is negatively related to firm size, stock prices, and stock liquidity, and positively related to stock price volatility and order size. This study uses implementation shortfall as a measure of the total trading cost, and this measure reveals that it is optimal to submit a limit order at the best quote: that is, a buy (sell) limit order at the best bid (ask). Finally, the results show that implementation shortfall is negatively related to firm size, stock prices, and stock liquidity, and positively related to firm volatility and order size.

The present comprehensive examination of trading costs contributes to the burgeoning body of literature exploring trading cost. In particular, the findings of this study provide a deeper understanding of the nature, determinants, and characteristics of trading costs in a pure order-driven, less-developed market, such as the Stock Exchange of Thailand. Therefore, this study is of interest to regulators, policy makers, brokers, and individual as well as institutional traders.

The remainder of the paper is organized as follows: Section 1.2 provides a literature review and discusses the hypotheses; section 1.3 provides details about the data, including sample selection and method; section 1.4 presents the empirical results of the study; and section 1.5 contains some conclusions.

1.2 Literature Review and Hypothesis Development

Trading costs are one of the most heavily researched areas in the market microstructure field. The focus of studies on trading costs is diverse: For example, some studies (e.g., Harris and Hasbrouck 1996; Peterson and Sirri 2002) compare the spreads for market and limit orders placed through the New York Stock Exchange's (NYSE) SuperDOT system; some studies (e.g., Cooney and Sias 2004; Werner 2003) compare the spreads and information about NYSE system orders, floor broker orders, and specialist orders; and some studies (e.g., Griffiths et al. 2000; Harris and Hasbrouck 1996) compare the trading costs of orders with different aggressiveness levels. Several studies examine trading costs in futures markets (e.g., Berkman et al. 2005; Frino and Oetomo 2005; Kurov 2005). A large number of studies (e.g., Bennett and Wei 2006; Bessembinder 1999, 2003b, 2003c; Bessembinder and Kaufman 1997a, 1997b; Boehmer 2005; Huang and Stoll 1996, 2001; SEC 2001; Venkataraman 2001) examine cross-exchange trading costs, particularly between NYSE and the National Association of Securities Dealers Automated Quotations (NASDAQ). Several studies (e.g., Chan and Lakonishok 1997; Chiyachantana et al. 2004; Conrad et al. 2003; Jones and Lipson 2001; Keim and Madhavan 1997, 1998; Perold and Sirri 1994; Wagner and Edwards 1993) investigate institutional trading costs.

1.2.1 Determinants of Price Impact Cost, Opportunity Cost, and Total Trading Cost

Previous research (e.g., Chiyachantana et al. 2004; Keim and Madhavan 1998; Wagner and Edwards 1993) finds a number of factors that affect spreads and, therefore, trading costs. This study divides factors that affect trading costs into two main variables: (1) decision variables, that is, factors that are determined by investors and traders (e.g., size and aggressiveness level of an order); and (2) exogenous variables, that is, factors outside the control of traders (e.g., stock-specific factors and market condition [i.e., bull, bear, or neutral]). Specifically, the relevant decision variables are order size and order aggressiveness level, and the stock-specific characteristics include market capitalization, volatility, and trading volume.

An aggressive order is expected to pay a higher price impact cost than a passive order because aggressive order traders require immediacy, and they need to pay for this immediacy (Griffiths et al. 2000). This discussion leads to the following hypothesis:

Hypothesis 1: The more aggressive the order, the larger the price impact (i.e., there is a positive relationship between the aggressiveness level of an order and the price impact of an order).

Easley and O'Hara's (1987) model suggests that a large-sized order incurs high trading costs. Keim and Madhavan (1997, 1998) provide empirical evidence about institutional equity trades that supports the claim that a large order has high price impact costs. Aggressive orders incur no opportunity cost,[9] and their cost,

[9] In general, an aggressive order refers to an order that get fully executed immediately upon submission. Therefore, an aggressive order will not have any unexecuted portions and incur no opportunity costs for unexecuted portions.

measured by implementation shortfall (i.e., a weighted average of price impact cost and opportunity cost), should have the same relationship to order size as price impact cost. For a limit order, as the size of the order increases, it becomes more difficult for the order to be filled, which leads to higher opportunity cost (i.e., the cost of the need to eventually transact the unfilled portions, usually at unfavorable prices). For a limit order, the opportunity cost is the main part of its total cost; therefore, the larger order size of the limit order should incur higher implementation shortfall cost.[10] These arguments lead to the following hypotheses:

Hypothesis 2: There is a positive (negative) relationship between the order size and price impact of an aggressive (passive) order.

Hypothesis 2.1: There is a positive relationship between the order size and opportunity cost of a passive order.

Hypothesis 2.2: There is a positive relationship between the order size and implementation shortfall of an order.

Bessembinder and Kaufman (1997a) and Keim and Madhavan (1997, 1998) find that trades in large-cap stocks cost less than trades in small-cap stocks. Griffiths et al. (2000) examine the Toronto Stock Exchange (TSE) and find that the overall trading cost, measured by implementation shortfall, is higher in small-cap stocks than in large-cap stocks. Griffiths et al. (2000) and Wagner and Edwards (1993) show that an order's filling rate is lower for small-cap stocks than for large-cap stocks, which leads to higher opportunity costs for trades in smaller stocks. For a limit order, the opportunity cost is the main part of its overall trading cost. Therefore, a limit order's overall trading cost, measured by implementation

[10]To compare trading costs across different aggressiveness levels, the well-known implementation shortfall measure (Perold 1988) is used in the present study. The implementation shortfall measure consists of two components: the cost of the executed portion of an order (i.e., price impact cost) and the cost of the unexecuted portion of an order (i.e., opportunity cost).

shortfall, is higher among small capitalization firms. These arguments lead to the following hypotheses:

Hypothesis 3: There is a negative (positive) relationship between firm size and the price impact of an aggressive (passive) order.

Hypothesis 3.1: There is a negative relationship between firm size and the opportunity cost of a passive order.

Hypothesis 3.2: There is a negative relationship between firm size and the implementation shortfall of an order.

In addition, research (Copeland and Galai 1983; Foucault 1999; Harris 1994; Ho and Stoll 1981) suggests that there are several determinants of spreads. These determinants therefore affect price impact cost because spread cost is a part of price impact cost paid by immediacy-demanding aggressive orders. Harris (1994) reports that there is a positive relationship between spreads and the inverse of stock prices, which leads to hypothesis 4:

Hypothesis 4: There is a positive (negative) relationship between the price impact of an aggressive (passive) order and the inverse of stock price.

Foucault's (1999) model suggests that posted spreads are positively related to stock volatility in a limit order market because when stock volatility increases the probability of being bagged becomes larger and forces limit order traders to demand larger compensation. Copeland and Galai (1983) show that the bid-ask spread is a positive function of return variance, and it is a result of the nature of the option embedded in limit orders. Ho and Stoll (1981) illustrate that spreads decrease in liquidity (when measured by dollar trading volume) and increase in risk (when measured by stock price volatility). Once again, because spread cost is a part of price impact cost paid by aggressive orders, volatility will affect price impact cost. These arguments lead to hypothesis 5:

Hypothesis 5: There is a positive (negative) relationship between stock price volatility and the price impact of an aggressive (passive) order.

According to the Foucault (1999) model, when the volatility of the stock increases, the risk of being picked off for limit order traders increases. Due to this reason, limit order traders post less attractive offers, and the cost of market order trading becomes more costly. Limit orders become more frequent than market orders. As a result, the proportion of limit orders in the order flow increases with stock volatility, and the limit order fill rate decreases with stock volatility. In addition, when stock volatility becomes larger, the adverse price change of the unexecuted portion of a limit order is likely to be larger. As a result, a limit order trader incurs a larger opportunity cost for more volatile stocks. This argument leads to hypothesis 5.1:

Hypothesis 5.1: There is a positive relationship between stock price volatility and the opportunity cost of a passive order.

Aggressive orders (e.g., market orders) incur no opportunity cost (Foucault 1999; Griffiths et al. 2000), and their cost, measured by implementation shortfall, should have the same relationship to stock price volatility as price impact cost. However, for a passive order, the relationship between stock price volatility and its implementation shortfall measure is an empirical question because according to the hypothesis 5 a passive order incurs a negative price impact cost (i.e., gains a price impact cost) from trading in more volatile stocks, but according to the hypothesis 5.1, a passive order incurs a higher opportunity cost when trading in high-volatile stocks. For a passive order, an opportunity cost is the principal part of its total cost (Griffiths et al. 2000). Therefore, the implementation shortfall cost of limit orders should be positively related to stock price volatility (see hypothesis 5.2):

Hypothesis 5.2: There is a positive relationship between stock price volatility and the implementation shortfall of an order.

1.2.2 Optimal Order Submission Strategy

Traders must decide what type of order to place when they want to buy shares. A market order demands immediacy from the counterparty and, therefore, incurs an implicit price for immediacy. On the other hand, a limit order is not guaranteed execution, and it faces an execution risk. To compute the cost of limit orders, therefore, it is necessary to consider the cost of not filling the entire order. In order to account for an entire transaction cost, including opportunity cost (i.e., the cost of not transacting), Perold (1988) develops the implementation shortfall measure of transaction costs.[11] Using the implementation shortfall measure, Harris (1998) develops a model that suggests it is optimal for most traders to place limit orders close to the market. Harris and Hasbrouck (1996), using a sample of NYSE SuperDOT orders, provide empirical evidence that limit orders submitted at the best quotes (i.e., buy [sell] limit orders priced at the best bid [ask]) perform best.[12] Griffiths et al. (2000), using data from the Toronto Stock Exchange, reach conclusions that are similar to Harris and Hasbrouck (1996). However, both studies use data from markets with market makers. Unlike NYSE or TSE, the Stock Exchange of Thailand uses a centralized electronic automatching system that does not require designated market makers. Therefore, the present study examines

[11]See Harris (1998, 2003) for a discussion about the relative merit of the implementation shortfall measure.

[12]The performance is based on the ex ante performance measure proposed by Harris and Hasbrouck (1996). The measure is conceptually similar to the implementation shortfall measure adopted in the present study. The only difference is that the Harris and Hasbrouck's measure uses the opposite-side quote prevailing at the time the order was submitted as a benchmark price, while the shortfall measure used in the present study uses the mid-quote prevailing at the order submission time as a benchmark price.

whether the optimal order submission strategy reported for NYSE and TSE also applies to a pure order-driven market, such as the Stock Exchange of Thailand:

Hypothesis 6: An implementation shortfall is minimized when traders submit buy (sell) orders at the best bid (ask).

1.3 Data and Methodology

1.3.1 Data

The data used in the present study are obtained from two files: an order file, which represents the orders submitted for all securities traded through an automatic order matching system (AOM) from January 2, 1997 to December 31, 1997; and a trade file, which records the transactions of orders submitted for all securities through AOM from January 2, 1997 to December 31, 1997. The data cover all securities traded on SET (i.e., 457 common stocks, 39 warrants, 70 unit trusts, and 170 foreign stocks). However, in order to ensure that the limit order book has bid-ask quotes for most periods, only 79 liquid stocks are analyzed in this study.[13] Specifically, the stocks examined in the present study must have 144 active trading days per year, with an active trading day defined as a day with a minimum of 25 trades. Although the number of covered stocks is approximately 17% (79/457) of the whole sample of stocks traded on SET, the market capitalization and trading volume of the 79 selected stocks cover approximately 70% of the whole stock sample (i.e., 457 issues) during 1997[14].

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[13]Ding and Charoenwong (2003) suggest that spreads of thinly traded futures contracts computed from days with trades are more informative than those computed from days without trades.

[14] As a robustness check, we re-run the entire analysis on additional 62 stocks. The results for the 62 stocks are generally qualitatively similar to those for the original 79 stocks. It may not be meaningful to perform robustness tests on *all* omitted firms because about two-thirds of the omitted firms are very illiquid (i.e., most of them have no more than 5 trades a

The SET index plummeted during most of the sample period (i.e., 1997) as a result of the Asian financial crisis. Only 95 of the 247 trading days in 1997 have positive open-to-close price changes. As Harris and Hasbrouck (1996) suggest, comparisons of the performance of buy and sell orders during periods of sharply rising or falling trends are not meaningful. Therefore, the analysis in the present study is based on a return-matched subsample: 77 days[15] with positive open-to-close price changes are compared to 77 days with negative open-to-close price changes. Therefore, the final sample consists of 79 stocks over 154 return-matched days. By construction, the distribution of open-to-close returns in the final sample is almost perfectly symmetric, with a mean, median, and skewness of nearly 0.

Data with several types of errors are excluded from the analyses. First, orders with negative spreads are deleted[16]. Opening transactions are also excluded because the opening transactions on SET occur under a call auction system, which differs from the continuous trading system applied throughout the rest of the trading day. In addition, orders submitted during morning- and afternoon-pre-opening periods (i.e., before the batch trading of respective periods) and after the close of the market are excluded from the analyses.

1.3.2 Methodology

1.3.2.1 Aggressiveness Level Classification

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day). Instead, the criteria for stocks to be included in our analyses are relaxed. Specifically, we now require a stock to have 120 active trading days instead of the original 144, where an active trading day is a day with a minimum of 10 trades (from the original restriction of 25 trades a day). With the relaxed restriction, those 62 firms are obtained.

[15]In the present study, 77 days with positive open-to-close price changes (instead of the whole 95 days with positive open-to-close price changes) is selected because 18 days with positive open-to-close price changes cannot be matched to days with negative open-to-close price changes.

[16] The negative spread observations are errors in data (i.e., keying errors).

Biais et al.'s (1995) order aggressiveness classification system is extended in the present study, and the orders are divided into seven different categories ranked by the level of aggressiveness. A Category 7 buy (sell) order is the most aggressive level because the order price is greater (less) than the best ask (bid) price, and the size of the order exceeds the depth at the best ask (bid). A Category 6 order is the second-most aggressive level because its price is equal to the best ask (bid), but the size of the order exceeds the depth at the best ask (bid). A Category 5 buy (sell) order is an order with a price that is equal to or even greater (less) than the best ask (bid), and the size of the order is smaller than the best ask (bid) depth. Although Category 5 to 7 market orders will be immediately executed, only Category 5 is executed in full, while Category 6 and 7 orders are executed in part, with the unfilled portion of the orders remaining as limit orders.[17]

Categories 1 to 4 are essentially limit orders (i.e., not immediately executed). Category 4 orders have prices that lie between the best bid and ask. Category 3 buy (sell) orders have prices equal to the best bid (ask). Category 2 buy (sell) orders have prices less (greater) than the best bid (ask) but greater (less) than the third best bid (ask).[18] Category 1 buy (sell) orders have prices less (greater) than the third best bid (ask). Only the best three quotes in real time are visible on SET, and a Category 1 order is invisible to participants on SET.

1.3.2.2 Price Impact Calculation

Following Griffiths et al. (2000), the price impact of an order is measured as the percentage change from a true or unperturbed value of a security to the

[17]To be more exact, Category 7 orders may or may not be executed in full, depending on the limit prices and depths at the next-step quotes.
[18]The third-best quote is used as the cutoff point because it is the last quote that is shown on the screen and still visible to all participants on SET.

volume-weighted average executed prices of the shares filling the order. The pretrade benchmark price is used as a proxy of the true value of a security.[19] In the present study, the pretrade benchmark is the mid-point of the quotes prevailing at the time of order submission.[20] In particular, the price impact is mathematically defined as follows:

$PI = \log(av.price / mid - quote)$ for a buy order

$PI = \log(mid - quote / av.price)$ for a sell order

where *PI* refers to the price impact of an order, *av.price* refers to the volume-weighted average of the prices of the shares filling the order, and *mid-quote* refers to the mid-point quote immediately before the order is submitted.

1.3.2.3 Opportunity Cost Calculation

When a market order is submitted, execution is guaranteed. Unlike a market order, a limit order encounters non-execution risk. Unexecuted limit orders (including partially executed limit orders) cannot be neglected because they represent the very real costs of foregone trades (i.e., opportunity costs). To precisely measure these costs, however, detailed knowledge of the traders' investment objectives is required. In order to calculate opportunity costs (i.e., the cost of not transacting), the present study uses the approach employed by Griffiths et al. (2000), Handa and Schwartz (1996), and Harris and Hasbrouck (1996).

[19]Alternative common benchmarks of the true value of a security include a post-trade benchmark, opening price, closing price, and daily volume-weighted average price (VWAP). The discussions about the relative merits of these benchmarks can be found in Harris (2003) and Chan and Lakonishok (1993, 1995).
[20]Several studies (e.g., Werner 2003) use the mid-quote at the time of the execution as the pretrade benchmark because they do not have details about the time of order submission. This problem is common in studies that employ TAQ data. Using the mid-quote at the time of order submission is conceptually more appropriate. Therefore, the present study improves on these studies.

Specifically, a fill price is assigned to orders not completely filled because of expiration or cancellation. This approach assumes that the trader is precommitted to trade in stocks: That is, the number of shares demanded in the order is the trader's desired number of shares to trade, and the unexecuted limit orders must be filled upon expiration or cancellation. On SET, orders that are not completely filled at the end of the trading day automatically expire. Therefore, it is assumed that the unexecuted portions of expired buy (sell) orders are filled at the closing ask (bid) price. In addition, if the size of the unfilled portion of a buy (sell) order exceeds the depth of the close ask (bid) price, the portion in excess of the available depth is assumed to be completely filled at the next minimum tick size step.

A slightly different approach is used for cancelled orders. Ideally, a fill price assigned to the cancelled portion of an order should be the opposite-side quote prevailing at the time of order cancellation.[21] Unfortunately, the time of cancellation of an order is unavailable in the data used in the present study. To mitigate any biases caused by the unavailability of the time of order cancellation, the time until order cancellation is estimated. Specifically, for each aggressiveness category, the time until cancellation (i.e., the duration an order is displayed until it is cancelled) is estimated using the average time to last fill of the executed portions of limit orders.[22] A cancelled portion of a buy (sell) order is filled at the best ask (bid) price prevailing at the estimated cancellation time if the best ask (bid) price is greater (less) than the order price; otherwise, if the best ask (bid) price prevailing at the estimated cancellation time is equal to or less (greater) than the buy (sell) order price, the cancelled portion is assumed to be filled by a market order at the initial

[21]Griffiths et al. (2000) use the opposite quotes 5 seconds after the order is cancelled as the assumed fill price.
[22]The figures are shown in Table 1.1.

submission time. As in the case of expired orders, the size of the cancelled portion of an order is taken into account: That is, if the size of the cancelled portion of a buy (sell) order exceeds the depth of the best ask (bid) price prevailing at the estimated cancellation time, it is assumed that the portion in excess of the available depth can be fully filled at the next step price.

The approach used to assign a fill price to the uncompleted portion of a limit order assumes that this unexecuted portion is filled by a resubmitted market order that executes against the opposite-side quote at the time of order cancellation or expiration.[23] According to Harris and Hasbrouck (1996), this approach almost certainly exaggerates the penalty incurred by execution failures.[24] In reality, a fraction of the unfilled portions of expired/cancelled limit orders are replaced by market orders. Some of those orders, of course, are replaced instead by more aggressively priced limit orders, or by nothing since some limit order traders are reluctant to trade at different prices from their desired prices. Hence, the approach is most appropriate for precommitted traders: that is, those who use limit orders to lower their trading costs but must trade before a certain deadline (e.g., a day). These traders use market orders or more aggressively priced limit orders after their initial limit orders fail to be executed. Furthermore, it is not possible to measure the cost of buying/selling stocks for a very large order that uses multiple split orders because the originally desired size of this type of order is not known.

[23]Some may argue that assuming a market order always executes against the opposite-side quote overstates the true economic loss because market orders often execute at inside-quote prices (i.e., receive price improvement). This concern is not applicable on the Thai stock market: That is, in the Stock Exchange of Thailand, market orders always execute at the quoted prices.

[24]The cost of trades (i.e., opportunity cost and implementation shortfall cost) of limit orders computed in the present study could be overestimated, to some extent. However, the potential biases from the overestimation of opportunity cost do not affect the main results of this study. In the Optimal Order Submission Strategy section, a discussion about why the main results of this study will not be affected by the biases from the overestimation of opportunity cost is provided.

1.3.2.4 Implementation Shortfall Calculation

The implementation shortfall measure (Perold 1988) is used in the present study to assess which aggressiveness level of orders has the lowest overall costs.[25] The implementation shortfall measure has two basic components: execution cost and opportunity cost. An implementation shortfall can be calculated as the opportunity cost of the unfilled part of an order plus execution cost (i.e., the price impact cost of the filled part of an order).

1.3.2.5 Regression Analysis

The following cross-sectional regression is conducted to test hypotheses 1 to 6 while controlling for other factors:

$$Y_i = \sum_{j=1}^{7} [c_j I_{i,j} + c_{j+7} I_{i,j} \times Buy_{i,j} + c_{j+14} I_{i,j} \times FirmSize_{i,j} + c_{j+21} I_{i,j} \times Volatility_{i,j} + c_{j+28} I_{i,j} \times PriceInverse_{i,j} + c_{j+35} I_{i,j} \times OrderSize_{i,j} + c_{j+42} I_{i,j} \times AvTrdVal_{i,j}] + \varepsilon_i ,$$

(1)

where Y_i denotes two measures of trading costs (i.e., price impact cost [PI_i] and implementation shortfall cost [IS_i]); PI_i equals the price impact of order i, with $ln(P_i /M_i)$ for buys orders and $ln(M_i /P_i)$ for sell orders; IS_i equals the implementation shortfall of order i; P_i equals the volume-weighted average of the trade price for order i; M_i equals the mid-point quote immediately before the submission of order i; $I_{i,j}$ equals a dummy variable equal to 1 if the aggressiveness of order i is Category j and 0 if otherwise, where j equals {1, 2, 3, 4, 5, 6, 7}, j equals 1, the most passive order, and j equals 7, the most aggressive order; Buy_i

[25] For the application of the implementation shortfall measure, see Chiyachantana et al. (2004), Griffiths et al. (2000), Perold and Sirri (1994), and Wagner and Edwards (1993), among others.

equals a dummy variable equal to 1 if a buy order and 0 if a sell order; $Firmsize_i$ equals the natural logarithm of the market capitalization of a firm at the end of 1996; $Volatility_i$ equals the standard deviation of the daily return of a stock in 1996; $PriceInverse_i$ equals the inverse of a stock price, defined as 100 times the inverse of the mid-point quote prevailing at the time of order submission, $(100/M_i)$; $Ordersize_i$ equals the order size divided by the average daily trading volume over the recent 5 trading days; $AvTrdVal_i$ equals the average daily trading value of a stock over 1996; and c denotes the coefficient of each explanatory variable.

1.4 Empirical Results

1.4.1 Descriptive Statistics of Order Classification

Table 1.1 presents the descriptive statistics about the order classifications. The total number of orders is divided evenly between buy and sell orders, with approximately 2.6 million orders for both buy and sell orders. Category 3 orders are the most frequent type of buy and sell orders, constituting slightly more than 25% of all orders submitted. Category 5 orders are the second-most frequent type of orders, constituting slightly less than 25% of all orders. Category 2 and Category 1 orders are the third- and fourth-most frequent type of orders, constituting approximately 20% and 16% of all orders, respectively. The two most aggressive types of orders (i.e., Category 7 and Category 6 orders) represent only 0.28% (0.26%) and 5.63% (5.86%) of all buy (sell) orders, respectively. Although small in terms of the number of orders, Category 7 and Category 6 orders constitute approximately 13.5% (15.5%) of the total buy (sell) volume (see Table 1.1, column 6) because Category 7 and Category 6 orders have much larger average sizes compared to the other categories. For example, for a buy-side order, the average size of a Category 6 order is 3.3 times (2 times) as large as a typical Category 5 (Category 3) order (see Table 1.1, column 5). Table 1.1 also presents the relative order size, which lends further support to the fact that Category 7 and Category 6 orders are relatively large: That is, the relative order sizes of Category 7 and Category 6 orders are 5.89% (5.97%) and 2.29% (2.20%) for buy (sell) orders, respectively.

The analysis of Category 4 orders reveals an interesting result: In terms of relative order size and the average number of filling trades of executed orders, a Category 4 order becomes disproportionately large. For example, for the buy side, the average size of a typical Category 4 order is 5,183 shares, while a typical Category 3 order is 6,753 shares. The relative order size of a typical Category 4 order, however, is 1.58%, which is larger than a typical Category 3 order (1.07%). A Category 4 order also has a higher average number of filling trades than Category 3 and Category 2 orders. Note also that the average size of a firm that attracts Category 4 orders is 32,081 million baht, which is substantially less than the size of firms that typically attract Category 3, 2, or 1 orders. This suggests that Category 4 orders are more prevalent among less-liquid (i.e., low-trading volume), small stocks. This result is considered intuitive because a Category 4 order is an order whose price is between the best bid and ask prices, a situation that is more prevalent among less-liquid, small stocks.

The filling rate for sell orders is much higher than the filling rate for buy orders because the size of a sell order is, on average, smaller than a buy order (i.e., 5,408 shares for sell orders and 5,993 shares for buy orders). In addition, sell orders are typically smaller in limit-order-type categories (i.e., aggressiveness level 1 to 4), which are the categories that do not get executed immediately upon submission.

The results also show that sell orders are, on average, executed slightly more quickly than buy orders (i.e., 21 minutes for sell orders versus 21.8 minutes for buy orders).

The average percentage of filling rate for limit order categories declines as order aggressiveness decreases (e.g., from Category 4 to Category 1). For example, for a limit buy (sell) order at the best bid (ask), approximately 42% (50%), on average, of the total number of shares are traded. The fill rate drops significantly when an order is priced away from the best quotes (i.e., Category 2 and Category 1). The low execution rates of limit orders indicate that limit order traders face a substantial execution risk: that is, the risk of not getting transacted.

The results show that the two most aggressive orders and Category 4 orders are more prevalent among small firms than among large firms (see Table 1.1, column 9). The average size of firms that attract Category 7, 6, and 4 orders are 29,616 million baht, 33,993 million baht, and 32,083 million baht for buy orders, respectively, while the average size of firms that attract passive orders are more than 40,000 million baht for buy orders. The results also hold for sell orders.

The average time to first execution for the three most aggressive orders is 0 by definition, but the average time to last execution are 2.3 minutes and around 9 minutes for Category 7 and Category 6 buy orders, respectively. For the limit-order-type categories, the average time to disposition of executed orders is higher as aggressiveness decreases.

1.4.2 Determinants of Trading Costs

Table 1.2 presents the price impact of executed orders. The results of buy orders[26] indicate that the price impact increases as the aggressiveness level increases, supporting hypothesis 1. Moreover, the magnitude of the price impact is negatively related to firm size, stock price, and the average trading value of stocks, but it is positively related to stock price volatility and order size. For example, for the large firm size group, which has an average market capitalization of 56,305 million baht (approximately US$1.4 billion), the price impact of buy orders ranges from 1.21% for the most aggressive orders to -4.00% for the least aggressive orders. For small-sized stocks with an average market capitalization of 2,889 million baht (equivalent to US$72 million), the price impact of buy (sell) orders ranges from 1.63% for Category 7 orders to -6.14% for Category 1 orders.

The results in Table 1.2 confirm hypotheses 2, 3, 4, and 5. For orders that result in immediate execution (i.e., marketable limit orders with aggressiveness levels of 5 to 7), the price impact is negatively associated with firm size, stock price, and average trading value of stocks, but it is positively related to volatility and order size (see Table 1.2). For limit orders, the converse relationships are true. For example, for small-capitalization, highly volatile, low-priced, less-liquid stocks, a market order becomes more expensive (i.e., a market order pays more for immediacy in these stocks), while a limit order profits more from supplying immediacy (i.e., the price impact of a limit order becomes more negative for these stocks).

The relationship between an order size and the price impact of various aggressiveness levels is as expected. Large-sized market orders pay a higher

[26]The results in Table 1.2 are for buy orders only. The results for sell orders are not reported because they are virtually identical to the results for buy orders.

immediacy price than small-sized market orders. This is consistent with the result in Wagner and Edwards' (1993) study. The immediacy prices paid by market orders are profits for executed passive orders (i.e., Category 1 to 4 orders), and large-sized limit orders obtain a higher immediacy price than small-sized limit orders.

Table 1.3 presents the relationship between the unfilling rate and its determinants (i.e., stock/order characteristics) across all order aggressiveness levels. The results discussion, however, focuses on the relationship between the unfilling rate and its determinants among limit orders because the unfilling rate is much more relevant to limit orders (i.e., Category 1 to 4) than to market orders (i.e., Category 5 to 7). As seen in Table 1.3, the unfilling rate increases as order aggressiveness decreases. By definition, Category 5 orders have a 0 nonexecution rate. The average unfilling rate for Category 6 orders ranges from 3.2% to 9.1%, while the average unfilling rate for Category 7 orders ranges from 0% to 2.6%. For limit orders, the unfilling rate generally increases when orders become more passively priced. For example, even when the buy order matches the best bid (i.e., a Category 3 order), approximately 40% of the order is not filled. When the buy order is priced below the best bid, more than 70% of the order is not filled, which suggests that limit order traders encounter a considerable nonexecution risk and a substantial opportunity cost. Orders for small-cap/low-trading-value stocks have a higher unfilling rate. This is the cost of the illiquidity of these stocks. Large-volume orders have a higher unfilling rate, reflecting the difficulty in locating enough shares to complete large orders. Finally, neither stock price volatility nor stock price has a clear impact on an order's unfilling rate.

Table 1.4 reports the adverse price change of the unexecuted portion of orders. The adverse price change is the cost of the need to eventually fill the uncompleted portion of the order by an aggressive order, and it is measured by the adverse percentage price change from the mid-point quote at the time of order submission to the assigned filled price. The adverse price change measures the cost of adverse selection arising from the nature of the option embedded in limit orders. When a limit order to buy (sell) is placed, the market is given a free put (call) option. As a result, the market will act strategically against the limit order. The adverse price change captures the adverse selection cost through the trades the market chooses not to transact. The results in Table 1.4 suggest that the adverse selection problem associated with the unfilled portion of orders is more severe in small-cap, highly volatile, low-priced, less-liquid stocks. Finally, large orders face higher adverse selection problems.

The opportunity cost shown in Table 1.5 is formed by the adverse price change percentage in Table 1.4 and the unfilling rate in Table 1.3. The opportunity cost in Table 1.5 is the product of the adverse price change percentage in Table 1.4 and the corresponding cell of the unfilling rate in Table 1.3. Table 1.5 shows that there is a sizable opportunity cost associated with limit orders (i.e., Category 1 to 4), and small-cap orders have a higher opportunity cost, consistent with hypothesis 3.1. For example, for Category 3 orders, the opportunity cost ranges from 0.62% for the large-firm group to 1.39% for the small-firm group. This is also reflected by the high (low) unfilling rate in Table 1.3 coupled with the high (low) adverse price shift in Table 1.4 of small (large) firms. This result is consistent with results in studies conducted by Griffiths et al. (2000) and Wagner and Edwards (1993). As hypothesized, opportunity cost is positively related to order size (hypothesis 2.1) and stock price volatility (hypothesis 5.1). Furthermore, opportunity cost is negatively related to stock price and negatively associated with the liquidity of a stock (as measured by daily average trading value). In addition, the results in Table 1.5 show very low opportunity costs for market orders. By definition, Category 5 orders have a 0 opportunity cost due to a 0 unfilling rate. The low opportunity costs of Category 6 and 7 orders are caused almost entirely by the low unfilling rates of these orders (see Table 1.3). The results for sell orders largely resemble the results for buy orders.

The opportunity cost in Table 1.5 is the cost of the unexecuted portion of an order, while the price impact in Table 1.2 (and multiplied by the filling rate percentage) forms the cost of the executed portion of an order. The implementation shortfall measure (Perold 1988) combines the cost of the unexecuted portion of an order and the price impact and produces a total trading cost.

Table 1.6 shows the implementation shortfall of orders, and it reveals that a large order (hypothesis 2.2) for small-capitalization (hypothesis 3.2), high-volatile (hypothesis 5.2), low-priced, low-average-trading-value stocks incurs a high shortfall cost. This result holds true for both market and limit orders as well as for all aggressiveness levels. For market orders, the price impact cost is the main part of the implementation shortfall cost; therefore, for market orders, the relationship between stock/order characteristics and the price impact cost is the same as the relationship between stock/order characteristics and the implementation shortfall cost.

As shown in Table 1.2, a limit order gains more immediacy price from small-cap, highly volatile, low-priced, illiquid stocks. However, using implementation shortfall as a measure of trading cost for a limit order (as shown in

Table 1.6) produces results contrary to the results in Table 1.2. Even though an executed limit order obtains a higher immediacy price from small-cap, highly volatile, low-priced, illiquid stocks, the nonexecution rate (as shown in Table 1.3) and the adverse price change of the unfilled portion (as shown in Table 1.4) of a limit order are high in these stocks. The nonexecution cost of a limit order is so large that it outweighs the favorable price impact (i.e., negative price impact) of the executed portion, making the total trading cost, as measured by the implementation shortfall, of a limit order positive and high in small-cap, highly volatile, low-priced, illiquid stocks (the relationship that is also shown in Tables 1.3 and 1.5). The results for a limit order show that the major cost of a limit order submission is the cost of not transacting. As a result, the cost of not transacting a limit order needs to be taken into account when comparing the transaction costs of market and limit orders.

1.4.3 Optimal Order Submission Strategy

As with Tables 1.5 and 1.6, Table 1.7 shows that there is a substantial opportunity cost for the unexecuted portion of a limit order. The cost of the unexecuted portion is a function of the unfilling rate of a limit order and the cost of aggressively trading the unexecuted portion at unfavorable prices. Consistent with Griffiths et al. (2000), the present study finds that the adverse price change rises monotonically with the level of order aggressiveness.[27] Table 1.7 demonstrates that for a limit order (i.e., order with aggressiveness level of 1 to 4) a favorable price impact is always more than offset by a positive opportunity cost, and the total cost

[27]This relationship is described in a manner different from the explanation offered by Griffiths et al. (2000). In the present study, this relationship merely represents a manifestation of the assumption underlying the calculation of the opportunity cost, as described in the Opportunity Cost Calculation section.

of trading, as measured by implementation shortfall, is positive. For example, Category 3 orders incur a negative cost of 0.37% for the executed portion of an order; however, approximately 43% of Category 3 orders go unexecuted and need to be filled at a cost of 0.84%. Therefore, the overall cost of Category 3 orders becomes 0.47%.

The implementation shortfall of market orders (i.e., orders with aggressiveness levels of 5 to 7) is similar in magnitude to the price impact measure because the dominant cost of market orders is the price impact cost (as a result of a very high completion rate). For Category 4 orders (i.e., a limit order that improves the current quote but does not result in immediate execution), the implementation shortfall is much higher than the implementation shortfall for the adjacent market order (i.e., Category 5) and the adjacent limit order (i.e., Category 3). The implementation shortfall value for a Category 4 order is 1.31%, while the implementation shortfall for Category 5 and Category 3 orders are 0.66% and 0.47% respectively. This finding indicates that perhaps there is no advantage to placing this type of limit order.

Table 1.7 shows that a limit order with an aggressiveness level of 3 has the minimum total trading cost when measured by the implementation shortfall cost, supportive of hypothesis 6.[28] This result holds true for both buy and sell orders. For

[28]As discussed in the Opportunity Cost Calculation section, our assumption behind opportunity cost computation could result in an overestimation of the opportunity cost for the unfilled part of limit orders. However, such overestimation does not affect our empirical findings that Category 3 orders incur the minimum shortfall cost. The opportunity cost is the main cost for limit orders (i.e., Category 1 to 4 orders). As shown in Table 1.7, with an (overestimated) opportunity cost, the total cost for Category 3 orders is still lower than market order categories (i.e., Category 5 to 7 orders), which strengthens our findings. Moreover, the adverse price change (i.e., the cost of the need to eventually execute the uncompleted portion of the limit order) is higher for Category 3 orders than Category 1 and 2 orders (this observation also holds true after controlling for differences in stock/order characteristics, as shown in Table 1.4). Therefore, the degree of overestimation should be even higher in Category 3 orders than in Category 1 or 2 orders. Therefore, our

buy orders, the total cost of trading using Category 3 orders is 0.47%, whereas the total cost of trading ranges from 0.62% to 1.48% for the remaining types of orders. In addition, Table 1.6 shows that after controlling for various types of stock characteristics and order sizes Category 3 orders still offer the lowest overall trading cost.[29] All in all, based on the results shown in Table 1.7 and Table 1.6, traders who want to minimize their trading costs should submit a buy (sell) limit order priced at the best bid (ask).

1.4.4 Multivariate Analyses

As a result of the high correlation among some regressors in equation 1, eight different regressions are conducted. Table 1.8 shows the results for the eight regressions. In panel A, the dependent variable is the price impact of executed orders, while in panel B, the dependent variable is the implementation shortfall of all orders (i.e., fully executed, partially executed, and unexecuted orders). Like the univariate results in Table 1.2, the multivariate results in panel A, Table 1.8 show that price impact is positively and significantly related to the aggressiveness level of an order (i.e., the intercept terms increase in value from C_1 to C_7). The chi-square tests suggest that the null hypothesis of the equality of the intercept terms is highly rejected. Panel A, Table 1.8 also indicates that for market orders (limit orders) price impact is negatively (positively) related to *FirmSize*. Again, the chi-square tests suggest that the null hypothesis of equality of the coefficients C_{15} to C_{21} is highly rejected. Furthermore, the most aggressive and passive types of orders

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findings that Category 3 orders have the minimum shortfall cost should not be affected (or even become stronger).

[29]In the multivariate analyses, the total trading cost among various aggressiveness levels is compared by simultaneously controlling for differences in stock/order characteristics, and this comparison shows that Category 3 orders incur the lowest total trading cost after these differences are controlled.

(i.e., Category 7 and Category 1) exhibit the greatest sensitivity of price impact to *FirmSize*, as suggested by the magnitude of C_{15} and C_{21} compared to C_{16} to C_{20}. This finding indicates that price impact is more sensitive to firm size for highly aggressive or highly passive orders than for less aggressive or less passive orders.

Panel A, Table 1.8 shows that for market orders (limit orders) price impact is positively (negatively) related to *Volatility*. Therefore, limit order traders benefit more from volatile stocks, and as a result, market order traders pay a higher immediacy price for volatile stocks. This is consistent with Foucault's (1999) model, which suggests that an increase in stock volatility forces limit order traders to ask for a larger compensation, and with Copeland and Galai (1983), who demonstrate that the bid-ask spread is a positive function of return variance as a result of the nature of the option embedded in limit orders. Moreover, comparing the magnitude of C_{22} and C_{28} to the magnitude of C_{23} to C_{27} shows that the most aggressive and passive orders exhibit the greatest sensitivity of price impact cost to *Volatility*. This is consistent with Table 1.2, and it implies that price impact is more sensitive to stock price volatility for highly aggressive or highly passive orders than for less aggressive or less passive orders.

For market orders (limit orders), price impact is positively (negatively) related to *OrderSize*. A market order trader pays a higher immediacy cost for larger-sized orders. This is consistent with the model proposed by Easley and O'Hara (1987) and with the empirical results from studies that examine institutional trades (e.g., Keim and Madhavan 1997, 1998).

Panel A, Table 1.8 shows that for market orders (limit orders) price impact is positively (negatively) related to *PriceInverse*. In other words, the price impact cost of a market order is larger for stocks with low prices, and a limit order benefits more from stocks with low prices. This is consistent with Harris (1994), who reports that spread is positively related to the inverse of the stock price. Furthermore, the most aggressive and most passive orders exhibit the greatest sensitivity of price impact to *PriceInverse*, given the magnitude of C_{42} and C_{36} compared to C_{37} to C_{41}. This finding suggests that price impact is most sensitive to stock prices for highly aggressive or highly passive orders, which is consistent with the univariate results shown in Table 1.2.

Finally, the results in panel A, Table 1.8 show that for the three categories of aggressive (passive) orders, *AvTrdVal*, the average trading value of stocks, is negatively (positively) related to price impact. Liquid stocks (i.e., stocks with high *AvTrdVal*) are less costly to market order traders; nonetheless, limit order traders benefit less from liquid stocks. In addition, the results illustrate that order aggressiveness affects the relationship between *AvTrdVal* and price impact: That is, the relation is strongest for the most aggressive (i.e., Category 7) and the most passive (i.e., Category 1) orders. This implies that the price impact costs for highly aggressive/passive orders become more sensitive to the liquidity of stocks than the price impact costs for less aggressive/passive orders.

The results from the regression analysis of the determinants of implementation shortfall are shown in panel B, Table 1.8. For each of the eight regressions, $Intercept_3$, the intercept term for a Category 3 order, is lowest compared to the remaining six intercept terms. This result shows that the implementation shortfall is minimized for an order with an aggressiveness level of 3 even after other determinants of the implementation shortfall are controlled.

In general, the multivariate results shown in panel B, Table 1.8 resemble the univariate results shown in Table 1.6: That is, the implementation shortfall is negatively related to firm size, positively related to stock price volatility, positively related to order size, positively related to the inverse of stock prices, and negatively related to the dollar trading volume of stocks. The multivariate results indicate that there is a significantly negative relationship between *FirmSize* and an implementation shortfall for all categories of orders. This is consistent with Table 1.6 because it is more expensive to trade smaller stocks after order aggressiveness and other determinants of the implementation shortfall are controlled. The relationship between price volatility and implementation shortfall is positively significant for all types of orders, which suggests that it is more expensive to trade volatile stocks. Moreover, the most aggressive orders exhibit the greatest sensitivity of implementation shortfall cost to stock price volatility. For example, for Model 8, the C_{28} is 35.58, larger than the magnitudes of the remaining coefficients, C_{22} to C_{27}. This implies that an implementation shortfall is most sensitive to stock price volatility for the most aggressive orders, which is consistent with Table 1.6.

The results in panel A, Table 1.8 show that there is a significantly positive relationship between *OrderSize* and an implementation shortfall for all levels of aggressiveness, which indicates that large-sized orders incur higher total trading costs. The results also illustrate that an implementation shortfall is significantly and positively associated with *PriceInverse*. In other words, the shortfall cost of an order is larger for stocks with low prices. In addition, consistent with Table 1.6, the most aggressive order (i.e., Category 7 order) exhibits the greatest sensitivity of implementation shortfall to *PriceInverse*, given the magnitude of C_{42} relative to C_{36} to C_{41}. This indicates that for Category 7 orders low-priced stocks have much higher shortfall costs than high-priced stocks.

Finally, for a given category of orders, there is a significantly negative relationship between *AvTrdVal*, the average trading value of stocks, and an implementation shortfall. Liquid stocks (i.e., stocks with high average trading values) are less costly to traders. In addition, a comparison of the magnitude of Category 7 orders (i.e., C_{49}) and the magnitude of the remaining categories (i.e., C_{43}–C_{48}) shows that order aggressiveness affects the relationship between *AvTrdVal* and an implementation shortfall. The relationship is strongest for the most aggressive order (i.e., Category 7 order), which indicates that the shortfall cost for a Category 7 order is more sensitive to the liquidity of stocks than the shortfall cost for other categories of orders.

1.5 Conclusion

This study empirically examines and quantifies various components of trading costs incurred when trading 79 liquid stocks listed on the Stock Exchange of Thailand during 1997. The results of this study show that an aggressive (passive) order incurs a positive (negative) price impact cost for executed orders. In other words, an aggressive order (i.e., market order) pays an immediacy price, while an executed passive order (i.e., executed limit order) profits from supplying immediacy. In addition, five main factors that have a significant impact on determining the price impact cost are identified. For market orders, the price impact cost is negatively related to firm size, positively re low-priced, illiquid stocks, whereas passive order traders benefit more from these stocks.

For unmatched limit orders, however, there exists a sizable opportunity cost. The unexecuted portions of limit orders need to be filled at unfavorable prices as a result of an adverse selection problem associated with the unfilled portions. It is the opportunity cost of the unexecuted portions of limit orders that offsets the favorable executed price of the filled portions of limit orders and causes the overall trading cost of limit orders to become positive (i.e., incurs trading costs). The study also finds a relationship between stock/order characteristics and the opportunity cost of limit orders. For example, small-cap orders have a higher opportunity cost, which is consistent with the findings of Griffiths et al. (2000) and Wagner and Edwards (1993). Furthermore, opportunity cost is positively related to stock price volatility, negatively related to stock price, positively related to order size, and negatively related to the liquidity of a stock.

The present study suggests that implementation shortfall should be used as a trading cost measure to compare the total trading costs of orders with various aggressiveness levels because implementation shortfall takes into account the opportunity cost of the unfilled portions of limit orders. By using the implementation shortfall as a total trading cost measure, the present study demonstrates that it is optimal to submit a limit order at the best quote: that is, a buy (sell) limit order at the best bid (ask).

Finally, the multivariate results (from panel B, Table 1.8) show that an implementation shortfall is negatively related to firm size, positively related to stock price volatility, positively related to order size, positively related to the inverse of the stock price, and negatively related to the dollar trading volume of stocks. In other words, for any type of order aggressiveness, it is more expensive to trade large amounts of shares of small-cap, highly volatile, low-priced, illiquid stocks. In addition, the most aggressive order (i.e., Category 7 order) exhibits the greatest sensitivity of implementation shortfall to stock price volatility, the inverse of the stock price, and the average dollar trading volume of stocks.

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Table 1.1
Descriptive Statistics for Order Classifications

This Table shows the descriptive statistics for all orders for 79 stocks on the Stock Exchange of Thailand (SET) during 1997. Seven levels of order aggressiveness are defined. The figures in columns 3 to 9 are calculated from all orders (i.e., fully executed, partially executed, and unexecuted orders). The figures in columns 10 to 12 describe the disposition of executed orders only. Relative order size is calculated using the ratio of the number of shares demanded in an order to the 5-day moving average number of shares traded for a particular stock.

Type	Aggressiveness level	Number of orders	Number of orders as a percentage of total (%)	Average number of shares in order	Average number of shares in order as a percentage of total (%)	Relative order size (%)	(Volume-weighted) average percentage of filling rate (%)	Average size of firm to which orders belong (million baht)	Average number of filling trades of executed orders	Average time to first disposition of executed orders (minutes)	Average time to complete disposition of executed orders (minutes)
c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12
Panel A: Buy orders											
MB7	7	7,340	0.28%	18,903	0.89%	5.89%	95.0%	29,616	6.4	0.0	2.3
MB6	6	146,903	5.63%	13,432	12.62%	2.29%	87.8%	33,993	4.2	0.0	9.0
MB5	5	636,193	24.38%	4,084	16.61%	0.57%	100.0%	39,399	1.7	0.0	0.0
LB4	4	170,429	6.53%	5,183	5.65%	1.58%	50.2%	32,083	1.9	16.4	21.4
LB3	3	725,821	27.81%	6,753	31.34%	1.07%	41.6%	40,055	1.7	25.8	30.8
LB2	2	512,938	19.66%	6,594	21.63%	1.07%	16.1%	43,854	1.5	96.7	101.7
LB1	1	409,890	15.71%	4,299	11.27%	0.69%	6.6%	55,733	1.4	168.6	175.5
	Buy totals	2,609,514	100.00%	5,993	15,638,918,850	1.01%	48.6%	42,213	2.0	21.8	25.1
Panel B: Sell orders											
MS7	7	6,714	0.26%	20,489	0.98%	5.97%	96.5%	28,614	6.7	0.0	3.0
MS6	6	151,751	5.86%	13,458	14.59%	2.20%	92.0%	34,165	4.4	0.0	9.2
MS5	5	563,158	21.75%	4,551	18.30%	0.67%	100.0%	38,414	1.8	0.0	0.0
LS4	4	169,574	6.55%	4,921	5.96%	1.42%	71.3%	35,007	2.1	11.9	16.3
LS3	3	669,489	25.86%	5,480	26.20%	1.02%	50.4%	41,361	1.8	25.7	30.2
LS2	2	579,283	22.37%	5,119	21.18%	0.91%	19.1%	39,657	1.5	84.2	87.7
LS1	1	449,195	17.35%	3,987	12.79%	0.77%	7.4%	45,334	1.4	143.5	148.2
	Sell totals	2,589,164	100.00%	5,408	14,002,369 0 T,950	0.98%	55.1%	40,157	2.1	21.0	24.1
	Grand total	5,198,678		5,702	29,641,280,800	1.00%	51.7%	41,189	2.0	21.4	24.6

MB7 (MS7) is market buy (sell) orders with an order price higher (lower) than the best ask (bid) price and an order size larger than the shares available at the ask (bid). MB6 (MS6) is market buy (sell) orders with an order size larger than shares available at ask (bid) and an order price equal to the price at the ask (bid). MB5 (MS5) is market buy (sell) orders with order prices equal to the best ask (bid) and volumes smaller than the prevailing ask (bid) depth. LB4 (LS4) is limit buy (sell) orders with order prices higher (lower) than the best bid (ask) price but lower (higher) than the best ask (bid) prices. LB3 (LS3) is limit buy (sell) orders with order prices equal to the best bid (ask) prices. LB2 (LS2) is limit buy (sell) orders with order prices lower (higher) than the best bid (ask) price but higher (lower) than the third best bid (ask) prices. LB1 (LS1) is limit buy (sell) orders with order prices lower (higher) than the third best bid (ask) prices.

Table 1.2
Price Impact of Executed Orders

This Table shows the price impact of all executed orders for 79 stocks on the Stock Exchange of Thailand (SET) during 1997. Seven levels of order aggressiveness are defined. Price impact for buy (sell) orders is defined as the (minus of) the logarithm of the ratio of the volume-weighted average of the executed prices to the mid-point quote prevailing at the time of order submission. To group by firm size, the 79 stocks are ranked by market capitalization as of 31 December 1996. To group by volatility, the 79 stocks are ranked by volatility calculated using daily returns during 1996. To group by stock price level, the 79 stocks are ranked by price level ($ term) as of 31 December 1996. The 79 stocks are then sorted into three groups based on these three rankings (i.e., firm size, volatility, and stock prices). To group by order size, orders are ranked by their complexity, measured by the relative order size (i.e., order size is divided by the 5-day moving average trading volume of the ordered stock). The relative order sizes are sorted into three groups (i.e., small, medium, and large). To group by average trading value, the 79 stocks are ranked by their average trading values during 1997. Then the average trading values are sorted into three groups. The reported figure in each cell is the arithmetic mean of price impact, represented in percentage terms. Average Value refers to the average value of a particular category (e.g., 2,889 in the upper left cell is the averaged value of Small Firm in million baht). The results shown below are for buy orders only. The results for sell orders are not reported because they are virtually identical to those for buy orders.

Aggressiveness Level	Firm Size (million baht)			Volatility (annualized percentage)			Stock Price Level (baht)			Order Size (relative percentage)			Average Trading Value (thousand baht)		
	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Small	Medium	Large	Low	Medium	High
Average Value	2,889	11,298	56,305	31.9%	43.1%	55.6%	16.9	47.9	188.2	0.04%	0.22%	2.72%	3,562	10,360	61,904
MB7	1.63%	1.55%	1.21%	1.27%	1.43%	1.81%	1.93%	1.39%	1.26%	0.97%	1.11%	1.51%	1.69%	1.55%	1.15%
MB6	0.97%	0.72%	0.55%	0.62%	0.63%	0.83%	0.94%	0.61%	0.61%	0.51%	0.60%	0.75%	1.03%	0.79%	0.55%
MB5	1.08%	0.70%	0.50%	0.56%	0.61%	0.84%	0.95%	0.59%	0.54%	0.53%	0.66%	0.85%	1.16%	0.77%	0.54%
LB4	-0.03%	0.09%	0.08%	0.08%	0.06%	0.03%	0.13%	0.04%	0.03%	0.08%	0.07%	0.04%	-0.06%	0.07%	0.10%
LB3	-1.12%	-0.70%	-0.49%	-0.53%	-0.61%	-0.84%	-0.93%	-0.59%	-0.52%	-0.52%	-0.65%	-0.82%	-1.27%	-0.77%	-0.53%
LB2	-3.12%	-2.31%	-1.65%	-1.77%	-1.95%	-2.55%	-2.74%	-1.97%	-1.73%	-1.77%	-2.11%	-2.46%	-3.34%	-2.49%	-1.79%
LB1	-6.14%	-5.07%	-4.00%	-4.06%	-4.43%	-5.23%	-5.14%	-4.55%	-4.14%	-4.21%	-4.72%	-5.08%	-6.17%	-5.58%	-4.21%

MB7 (MS7) is market buy (sell) orders with an order price higher (lower) than the best ask (bid) price and an order size larger than the shares available at the ask (bid). MB6 (MS6) is market buy (sell) orders with an order size larger than shares available at ask (bid) and an order price equal to the price at the ask (bid). MB5 (MS5) is market buy (sell) orders with order prices equal to the best ask (bid) and volumes smaller than the prevailing ask (bid) depth. LB4 (LS4) is limit buy (sell) orders with order prices higher (lower) than the best bid (ask) price but lower (higher) than the best ask (bid) prices. LB3 (LS3) is limit buy (sell) orders with order prices equal to the best bid (ask) prices. LB2 (LS2) is limit buy (sell) orders with order prices lower (higher) than the best bid (ask) price but higher (lower) than the third best bid (ask) prices. LB1 (LS1) is limit buy (sell) orders with order prices lower (higher) than the third best bid (ask) prices.

Table 1.3
Unfilling Rate of Orders

This Table shows the unfilling rates of all orders for 79 stocks on the Stock Exchange of Thailand (SET) during 1997. Seven levels of order aggressiveness are defined. To group by firm size, the 79 stocks are ranked by market capitalization as of 31 December 1996. To group by volatility, the 79 stocks are ranked by volatility calculated using daily returns during 1996. To group by stock price level, the 79 stocks are ranked by price level ($ term) as of 31 December 1996. The 79 stocks are then sorted into three groups based on these three rankings (i.e., firm size, volatility, and stock prices). To group by order size, orders are ranked by their complexity, measured by the relative order size (i.e., order size divided by the 5-day moving average trading volume of the ordered stock). The relative order sizes are sorted into three groups (i.e., small, medium, and large). To group by average trading value, the 79 stocks are ranked by their average trading values during 1997. Then the average trading values are sorted into three groups. The reported figure in each cell is the arithmetic mean of unfilling rate, represented in percentage terms. Average Value refers to the average value of a particular category (e.g., 2,889 in the upper left cell is the averaged value of Small Firm in million baht). The results shown below are for buy orders only. The results for sell orders are not reported because they are virtually identical to those for buy orders.

Aggressiveness Level	Firm Size (million baht)			Volatility (annualized percentage)			Stock Price Level (baht)			Order Size (relative percentage)			Average Trading Value (thousand baht)		
	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Small	Medium	Large	Low	Medium	High
Average Value	2,889	11,298	56,305	31.9%	43.1%	55.6%	16.9	47.9	188.2	0.04%	0.22%	2.72%	3,562	10,360	61,904
MB7	1.2%	1.9%	2.4%	2.1%	1.8%	1.7%	2.0%	1.7%	2.0%	0.0%	0.4%	2.3%	1.5%	2.6%	1.8%
MB6	8.7%	7.2%	7.1%	7.7%	7.2%	7.6%	7.3%	7.1%	8.2%	3.2%	4.9%	9.0%	9.1%	8.6%	6.5%
MB5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
LB4	43.9%	40.7%	39.2%	40.4%	39.7%	42.5%	38.1%	40.1%	43.2%	32.2%	38.5%	45.9%	41.0%	43.3%	39.0%
LB3	46.5%	42.2%	39.8%	41.0%	40.9%	43.3%	44.4%	40.7%	41.0%	36.2%	39.8%	49.2%	46.9%	45.0%	39.8%
LB2	78.1%	73.3%	72.4%	74.2%	72.9%	73.7%	78.0%	71.4%	73.1%	67.5%	72.6%	80.3%	79.1%	76.5%	71.7%
LB1	91.3%	89.3%	90.9%	91.0%	90.8%	89.1%	92.0%	89.9%	90.5%	89.1%	90.7%	93.1%	92.2%	90.8%	90.2%

MB7 (MS7) is market buy (sell) orders with an order price higher (lower) than the best ask (bid) price and an order size larger than the shares available at the ask (bid). MB6 (MS6) is market buy (sell) orders with an order size larger than shares available at ask (bid) and an order price equal to the price at the ask (bid). MB5 (MS5) is market buy (sell) orders with order prices equal to the best ask (bid) and volumes smaller than the prevailing ask (bid) depth. LB4 (LS4) is limit buy (sell) orders with order prices higher (lower) than the best bid (ask) price but lower (higher) than the best ask (bid) prices. LB3 (LS3) is limit buy (sell) orders with order prices equal to the best bid (ask) prices. LB2 (LS2) is limit buy (sell) orders with order prices lower (higher) than the best bid (ask) price but higher (lower) than the third best bid (ask) prices. LB1 (LS1) is limit buy (sell) orders with order prices lower (higher) than the third best bid (ask) prices.

Table 1.4
Adverse Price Changes

This Table shows the percentage of adverse price changes of all orders for 79 stocks on the Stock Exchange of Thailand (SET) during 1997. Seven levels of order aggressiveness are defined. Adverse price changes for buy (sell) orders are defined as the (minus of) the logarithm of the ratio of the best ask (bid) price at the assumed cancellation time to the mid-point quote at the time of order submission if the best ask (bid) is higher than the order price. Otherwise (i.e., the best ask [bid] is lower [higher] than the order price), the unfilled part is assumed to be filled by a market order at the order submission time; therefore, adverse price changes for buy (sell) orders are the (minus of) the logarithm of the ratio of the best ask (bid) price at the time of order submission to the mid-point quote at the time of order submission. To group by firm size, the 79 stocks are ranked by market capitalization as of 31 December 1996. To group by volatility, the 79 stocks are ranked by volatility calculated using daily returns during 1996. To group by stock price level, the 79 stocks are ranked by price level ($ term) as of 31 December 1996. The 79 stocks are then sorted into three groups based on these three rankings (i.e., firm size, volatility, and stock prices). To group by order size, orders are ranked by their complexity, measured by the relative order size (i.e., order size divided by the 5-day moving average trading volume of the ordered stock). Then the relative order sizes are sorted into three groups (i.e., small, medium, and large). To group by average trading value, the 79 stocks are ranked by their average trading values during 1997. Then the average trading values are sorted into three groups. The reported figure in each cell is the arithmetic mean of the percentage of adverse price change. Average Value refers to the average value of a particular category (e.g., 2,889 in the upper left cell is the averaged value of Small Firm in million baht). The results shown below are for buy orders only. The results for sell orders are not reported because they are virtually identical to those for buy orders.

Aggressiveness Level	Firm Size (million baht)			Volatility (annualized percentage)			Stock Price Level (baht)			Order Size (relative percentage)			Average Trading Value (thousand baht)		
	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Small	Medium	Large	Low	Medium	High
Average Value	2,889	11,298	56,305	31.9%	43.1%	55.6%	16.9	47.9	188.2	0.04%	0.22%	2.72%	3,562	10,360	61,904
MB7	5.25%	4.77%	3.72%	1.32%	1.40%	1.81%	4.93%	3.94%	4.24%	0.76%	1.04%	1.56%	4.74%	4.82%	3.46%
MB6	3.95%	3.19%	2.64%	2.81%	2.95%	3.62%	3.79%	2.99%	2.80%	2.58%	2.81%	3.21%	4.04%	3.33%	2.64%
MB5	1.36%	0.96%	0.66%	2.05%	1.97%	4.16%	3.10%	1.94%	2.68%	1.46%	1.83%	2.56%	1.38%	1.06%	0.72%
LB4	3.58%	3.32%	2.73%	2.88%	2.99%	3.55%	3.70%	3.07%	2.83%	2.73%	2.96%	3.33%	3.74%	3.27%	2.77%
LB3	2.99%	2.01%	1.57%	1.63%	1.83%	2.46%	2.61%	1.82%	1.62%	1.70%	1.87%	2.26%	3.37%	2.06%	1.67%
LB2	2.18%	1.89%	1.58%	1.53%	1.75%	2.10%	1.91%	1.85%	1.53%	1.71%	1.69%	1.90%	2.24%	1.85%	1.67%
LB1	1.26%	1.26%	1.11%	1.08%	1.15%	1.34%	1.18%	1.26%	1.01%	1.16%	1.10%	1.28%	1.32%	1.13%	1.16%

MB7 (MS7) is market buy (sell) orders with an order price higher (lower) than the best ask (bid) price and an order size larger than the shares available at the ask (bid). MB6 (MS6) is market buy (sell) orders with an order size larger than shares available at ask (bid) and an order price equal to the price at the ask (bid). MB5 (MS5) is market buy (sell) orders with order prices equal to the best ask (bid) and volumes smaller than the prevailing ask (bid) depth. LB4 (LS4) is limit buy (sell) orders with order prices higher (lower) than the best bid (ask) price but lower (higher) than the best ask (bid) prices. LB3 (LS3) is limit buy (sell) orders with order prices equal to the best bid (ask) prices. LB2 (LS2) is limit buy (sell) orders with order prices lower (higher) than the best bid (ask) price but higher (lower) than the third best bid (ask) prices. LB1 (LS1) is limit buy (sell) orders with order prices lower (higher) than the third best bid (ask) prices.

Table 1.5
Opportunity Costs

This Table shows the opportunity costs of all orders for 79 stocks on the Stock Exchange of Thailand (SET) during 1997. The opportunity cost is calculated using the product of the percentage of unfilling rate (see Table 1.3) and adverse price change (see Table 1.4) for each corresponding cell. Seven levels of order aggressiveness are defined. To group by firm size, the 79 stocks are ranked by market capitalization as of 31 December 1996. To group by volatility, the 79 stocks are ranked by volatility calculated using daily returns during 1996. To group by stock price level, the 79 stocks are ranked by price level ($ term) as of 31 December 1996. The 79 stocks are then sorted into three groups based on these three rankings (i.e., firm size, volatility, and stock prices). To group by order size, orders are ranked by their complexity, measured by the relative order size (i.e., order size divided by the 5-day moving average trading volume of the ordered stock). Then the relative order sizes are sorted into three groups (i.e., small, medium, and large). To group by average trading value, the 79 stocks are ranked by their average trading values during 1997. Then the average trading values are sorted into three groups. The reported figure in each cell is the arithmetic mean of opportunity cost, represented in percentage terms. Average Value refers to the average value of a particular category (e.g., 2,889 in the upper left cell is the averaged value of Small Firm in million baht). The results shown below are for buy orders only. The results for sell orders are not reported because they are virtually identical to those for buy orders.

Aggressiveness Level	Firm Size (million baht)			Volatility (annualized percentage)			Stock Price Level (baht)			Order Size (relative percentage)			Average Trading Value (thousand baht)		
	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Small	Medium	Large	Low	Medium	High
Average Value	2,889	11,298	56,305	31.9%	43.1%	55.6%	16.9	47.9	188.2	0.04%	0.22%	2.72%	3,562	10,360	61,904
MB7	0.06%	0.09%	0.09%	0.03%	0.02%	0.03%	0.10%	0.07%	0.08%	0.00%	0.00%	0.04%	0.07%	0.13%	0.06%
MB6	0.35%	0.23%	0.19%	0.22%	0.21%	0.27%	0.28%	0.21%	0.23%	0.08%	0.14%	0.29%	0.37%	0.29%	0.17%
MB5	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
LB4	1.57%	1.35%	1.07%	1.16%	1.19%	1.51%	1.41%	1.23%	1.22%	0.88%	1.14%	1.53%	1.53%	1.42%	1.08%
LB3	1.39%	0.85%	0.62%	0.67%	0.75%	1.06%	1.16%	0.74%	0.66%	0.62%	0.75%	1.11%	1.58%	0.93%	0.66%
LB2	1.70%	1.39%	1.14%	1.13%	1.28%	1.55%	1.49%	1.32%	1.12%	1.16%	1.23%	1.53%	1.77%	1.42%	1.20%
LB1	1.15%	1.12%	1.01%	0.98%	1.04%	1.19%	1.09%	1.13%	0.92%	1.03%	0.99%	1.19%	1.22%	1.03%	1.05%

MB7 (MS7) is market buy (sell) orders with an order price higher (lower) than the best ask (bid) price and an order size larger than the shares available at the ask (bid). MB6 (MS6) is market buy (sell) orders with an order size larger than shares available at ask (bid) and an order price equal to the price at the ask (bid). MB5 (MS5) is market buy (sell) orders with order prices equal to the best ask (bid) and volumes smaller than the prevailing ask (bid) depth. LB4 (LS4) is limit buy (sell) orders with order prices higher (lower) than the best bid (ask) price but lower (higher) than the best ask (bid) prices. LB3 (LS3) is limit buy (sell) orders with order prices equal to the best bid (ask) prices. LB2 (LS2) is limit buy (sell) orders with order prices lower (higher) than the best bid (ask) price but higher (lower) than the third best bid (ask) prices. LB1 (LS1) is limit buy (sell) orders with order prices lower (higher) than the third best bid (ask) prices.

Table 1.6
Implementation Shortfall Measure of Orders

This Table shows the implementation shortfall values of all orders for 79 stocks on the Stock Exchange of Thailand (SET) during 1997. Seven levels of order aggressiveness are defined. To group by firm size, the 79 stocks are ranked by market capitalization as of 31 December 1996. To group by volatility, the 79 stocks are ranked by volatility calculated using daily returns during 1996. To group by stock price level, the 79 stocks are ranked by price level ($ term) as of 31 December 1996. The 79 stocks are then sorted into three groups based on these three rankings (i.e., firm size, volatility, and stock prices). To group by order size, orders are ranked by their complexity, measured by the relative order size (i.e., order size divided by the 5-day moving average trading volume of the ordered stock). Then the relative order sizes are sorted into three groups (i.e., small, medium, and large). To group by average trading value, the 79 stocks are ranked by their average trading values during 1997. Then the average trading values are sorted into three groups. The reported figure in each cell is the arithmetic mean of the implementation shortfall measure, represented in percentage terms. Average Value refers to the average value of a particular category (e.g., 2,889 in the upper left cell is the averaged value of Small Firm in million baht). The results shown below are for buy orders only. The results for sell orders are not reported because they are virtually identical to those for buy orders.

Aggressiveness Level	Firm Size (million baht)			Volatility (annualized percentage)			Stock Price Level (baht)			Order Size (relative percentage)			Average Trading Value (thousand baht)		
	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Small	Medium	Large	Low	Medium	High
Average Value	2,889	11,298	56,305	31.9%	43.1%	55.6%	16.9	47.9	188.2	0.04%	0.22%	2.72%	3,562	10,360	61,904
MB7	1.66%	1.61%	1.27%	1.32%	1.47%	1.86%	1.99%	1.43%	1.31%	0.97%	1.13%	1.57%	1.73%	1.62%	1.19%
MB6	1.23%	0.90%	0.69%	0.78%	0.80%	1.03%	1.15%	0.77%	0.78%	0.58%	0.70%	0.96%	1.31%	1.01%	0.68%
MB5	1.08%	0.70%	0.50%	0.56%	0.61%	0.84%	0.95%	0.59%	0.54%	0.53%	0.66%	0.85%	1.16%	0.77%	0.54%
LB4	1.55%	1.41%	1.12%	1.21%	1.23%	1.53%	1.49%	1.26%	1.24%	0.93%	1.18%	1.55%	1.50%	1.46%	1.14%
LB3	0.87%	0.47%	0.34%	0.37%	0.42%	0.64%	0.68%	0.42%	0.36%	0.30%	0.38%	0.74%	0.99%	0.54%	0.36%
LB2	1.02%	0.77%	0.68%	0.68%	0.75%	0.88%	0.89%	0.76%	0.65%	0.58%	0.65%	1.04%	1.08%	0.83%	0.69%
LB1	0.62%	0.58%	0.65%	0.62%	0.63%	0.62%	0.68%	0.67%	0.52%	0.57%	0.55%	0.84%	0.74%	0.51%	0.64%

MB7 (MS7) is market buy (sell) orders with an order price higher (lower) than the best ask (bid) price and an order size larger than the shares available at the ask (bid). MB6 (MS6) is market buy (sell) orders with an order size larger than shares available at ask (bid) and an order price equal to the price at the ask (bid). MB5 (MS5) is market buy (sell) orders with order prices equal to the best ask (bid) and volumes smaller than the prevailing ask (bid) depth. LB4 (LS4) is limit buy (sell) orders with order prices higher (lower) than the best bid (ask) price but lower (higher) than the best ask (bid) prices. LB3 (LS3) is limit buy (sell) orders with order prices equal to the best bid (ask) prices. LB2 (LS2) is limit buy (sell) orders with order prices lower (higher) than the best bid (ask) price but higher (lower) than the third best bid (ask) prices. LB1 (LS1) is limit buy (sell) orders with order prices lower (higher) than the third best bid (ask) prices.

Table 1.7
Analysis of Total Costs of Orders

This Table breaks down the implementation shortfall cost of all orders submitted on the Stock Exchange of Thailand (SET) during 1997. Seven levels of order aggressiveness are defined. Price impact for buy (sell) orders is defined as the (minus of) the logarithm of the ratio of the volume-weighted average of the executed prices to the mid-point quote prevailing at the time of order submission. The cost of the filled portion is the product of the percentage of orders filled and the price impact. Adverse price changes for buy (sell) orders are defined as the (minus of) the logarithm of the ratio of the best ask (bid) price at the assumed cancellation time to the mid-point quote at the time of order submission if the best ask (bid) is higher than the order price. Otherwise (i.e., the best ask [bid] is lower [higher] than the order price), the unfilled part is assumed to be filled by a market order at the time of order submission; therefore, adverse price changes for buy (sell) orders are the (minus of) the logarithm of the ratio of the best ask (bid) price at the time of order submission to the mid-point quote at the time of order submission. The cost of the unfilled portion (i.e., opportunity cost) is the product of the percentage of the unfilling rate and the percentage of adverse price changes. Implementation shortfall is defined as the sum of the cost of the filled portion and opportunity cost. The results shown below are for buy orders only. The results for sell orders are not reported because they are virtually identical to those for buy orders.

Aggressiveness Levels	Percentage of Orders Filled	Price Impact	Cost of Filled Portion	Percentage of Orders Unfilled	Adverse Price Change	Cost of Unfilled Portion (Opportunity Cost)	Implementation Shortfall
7	98.1%	1.43%	1.40%	1.9%	4.28%	0.08%	1.48%
6	92.5%	0.68%	0.63%	7.5%	3.12%	0.23%	0.86%
5	100.0%	0.66%	0.66%	0.0%	2.45%	0.00%	0.66%
4	59.3%	0.06%	0.04%	40.7%	3.12%	1.27%	1.31%
3	57.3%	-0.65%	-0.37%	42.7%	1.98%	0.84%	0.47%
2	26.5%	-2.06%	-0.54%	73.5%	1.78%	1.31%	0.76%
1	9.5%	-4.50%	-0.43%	90.5%	1.17%	1.05%	0.62%

MB7 (MS7) is market buy (sell) orders with an order price higher (lower) than the best ask (bid) price and an order size larger than the shares available at the ask (bid). MB6 (MS6) is market buy (sell) orders with an order size larger than shares available at ask (bid) and an order price equal to the price at the ask (bid). MB5 (MS5) is market buy (sell) orders with order prices equal to the best ask (bid) and volumes smaller than the prevailing ask (bid) depth. LB4 (LS4) is limit buy (sell) orders with order prices higher (lower) than the best bid (ask) price but lower (higher) than the best ask (bid) prices. LB3 (LS3) is limit buy (sell) orders with order prices equal to the best bid (ask) prices. LB2 (LS2) is limit buy (sell) orders with order prices lower (higher) than the best bid (ask) price but higher (lower) than the third best bid (ask) prices. LB1 (LS1) is limit buy (sell) orders with order prices lower (higher) than the third best bid (ask) prices.

Table 1.8
Multivariate Analyses of Price Impact of Executed Orders and Implementation Shortfall of Orders

This Table shows the coefficients (multiplied by 100), *p*-values, chi-square values λ^2 (i.e., statistics of tests of equality of coefficient values within groups), adjusted R^2, and the number of observations used in the seven GMM regression equations (i.e., each regression model is a variation of the full model shown below). In panel A, the dependent variable is the price impact of executed orders. In panel B, the dependent variable is the implementation shortfall value of orders (i.e., both executed and unexecuted orders). * and ** denote the significance levels of 5% and 1% respectively. The full equation is as follows;

$$Y_i = \sum_{j=1}^{7} [c_j I_{i,j} + c_{j+7} I_{i,j} \times Buy_{i,j} + c_{j+14} I_{i,j} \times FirmSize_{i,j} + c_{j+21} I_{i,j} \times Volatility_{i,j}$$
$$+ c_{j+28} I_{i,j} \times PriceInverse_{i,j} + c_{j+35} I_{i,j} \times OrderSize_{i,j} + c_{j+42} I_{i,j} \times AvTrdVal_{i,j}] + \varepsilon_i ,$$

where Y_i denotes two measures of trading costs (i.e., price impact cost [PI_i] and implementation shortfall cost [IS_i]); PI_i equals price impact of order; *i* equals $ln(P_i /M_i)$ for buys orders and $ln(M_i /P_i)$ for sell orders; IS_i equals the implementation shortfall of order *i*; P_i equals the volume-weighted average of the trade price for order *i*; M_i equals the mid-point quote immediately before the submission of order *i*; $I_{i,j}$ is a dummy variable equal to 1 if the aggressiveness of order *i* is Category *j* and 0 if otherwise, where *j* equals {1, 2, 3, 4, 5, 6, 7}, *j* equals 1 if it is the most passive order, and *j* equals 7 if it is the most aggressive order; Buy_i is a dummy variable equal to 1 if a buy order and 0 if a sell order; $Firmsize_i$ equals the natural logarithm of the market capitalization of a firm at the end of 1996; $Volatility_i$ equals the standard deviation of the daily return of a stock in 1996; $PriceInverse_i$ equals the inverse of a stock price, defined as 100 times the inverse of the mid-point quote prevailing at the time of order submission $(100/ M_i)$; $Ordersize_i$ equals the order size divided by the average daily trading volume over the recent 5 trading days; $AvTrdVal_i$ equals the average daily trading value of a stock over 1996; and c_j denotes the coefficient of each explanatory variable.

† denotes the significance level of 5% of H_0: $C_i = C_{i+6}$ within each group of independent variables.

<u>Panel A</u>: Price Impact

	Coefficients	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
		Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$
C_1	$Intercept_1$	-9.543**†		-2.089**†		-4.131**†		-3.141**†		-10.579**†		-5.152**†		-6.065**†		-2.088**†	
C_2	$Intercept_2$	-5.622**	3375.3**	-0.511**	1929.0**	-2.050**	21231.4**	-1.426**	16571.1**	-6.377**	2737.6**	-2.436**	904.2**	-3.001**	990.6**	-0.505**	1947.6**
C_3	$Intercept_3$	-2.145**	22521.5**	0.006	1438.4**	-0.669**	24411.5**	-0.432**	33818.9**	-2.596**	17955.4**	-0.725**	2456.2**	-0.991**	2784.0**	0.009	1418.3**
C_4	$Intercept_4$	-0.117**	4739.0**	-0.409**	532.6**	-0.217**	7349.0**	-0.506**	8.2**	-0.381**	4496.8**	-1.754**	55.7**	-2.156**	64.8**	-0.410**	542.8**
C_5	$Intercept_5$	2.269**	6123.0**	-0.195**	130.6**	0.653**	25785.8**	0.372**	1153.9**	2.650**	7804.7**	0.524**	275.3**	0.678**	387.2**	-0.203**	121.7**
C_6	$Intercept_6$	1.836**	743.2**	0.098**	843.4**	0.624**	45.2**	0.397**	45.9**	2.191**	573.3**	0.538**	0.4	0.750**	7.1**	0.082**	749.1**
C_7	$Intercept_7$	3.704**	511.0**	0.609**	131.3**	1.466**	2248.6**	1.207**	1583.4**	4.382**	597.8**	1.717**	148.0**	2.128**	161.2**	0.502**	87.2**
C_8	Buy_1	-0.420**†		-0.397**†		-0.347**†		-0.369**†		-0.435**†		-0.393**†		-0.405**†		-0.399**†	
C_9	Buy_2	-0.006	803.9**	0.011*	751.2**	0.029**	601.6**	0.027**	888.7**	-0.022**	810.5**	0.018**	958.4**	0.009**	978.9**	0.012**	764.2**
C_{10}	Buy_3	0.037**	80.0**	0.035**	23.9**	0.031**	0.1	0.035**	4.3	0.036**	153.7**	0.037**	24.6**	0.037**	53.6**	0.036**	23.7**
C_{11}	Buy_4	0.273**	1467.2**	0.271**	1445.9**	0.274**	1638.9**	0.264**	1530.1**	0.276**	1524.0**	0.281**	2193.4**	0.281**	2131.8**	0.271**	1427.5**
C_{12}	Buy_5	-0.014**	2062.6**	-0.011**	1974.5**	-0.018**	2234.4**	0.015**	1841.8**	-0.013**	2123.2**	0.016**	2615.9**	0.016**	2546.0**	-0.007**	1918.6**
C_{13}	Buy_6	0.045**	321.3**	0.045**	290.0**	0.044**	343.2**	0.046**	230.2**	0.045**	330.7**	0.045**	193.2**	0.045**	193.9**	0.044**	244.6**
C_{14}	Buy_7	-0.164**	102.1**	-0.110**	54.8**	-0.168**	107.2**	-0.128**	83.6**	-0.203**	149.0**	-0.128**	87.6**	-0.143**	102.6**	-0.109**	57.2**
C_{15}	$FirmSize_1$	0.532**†										0.188**†					
C_{16}	$FirmSize_2$	0.355**	769.2**									0.098**	136.2**				
C_{17}	$FirmSize_3$	0.146**	9253.7**									0.029**	566.4**				
C_{18}	$FirmSize_4$	-0.010**	3443.4**									0.124**	70.9**				
C_{19}	$FirmSize_5$	-0.161**	3042.7**									-0.016**	156.0**				
C_{20}	$FirmSize_6$	-0.123**	724.1**									-0.015**	0.3				
C_{21}	$FirmSize_7$	-0.221**	151.9**									-0.061**	29.4**				
C_{22}	$Volatility_1$			-79.238**†												-78.290**†	
C_{23}	$Volatility_2$			-59.664**	195.5**											-58.717**	189.7**
C_{24}	$Volatility_3$			-26.148**	3752.0**											-25.842**	3136.7**
C_{25}	$Volatility_4$			7.447**	1775.2**											7.424**	1737.5**
C_{26}	$Volatility_5$			32.719**	914.4**											32.052**	869.1**
C_{27}	$Volatility_6$			20.278**	814.3**											20.186**	742.1**
C_{28}	$Volatility_7$			37.221**	100.3**											36.151**	94.6**

Panel A: Price Impact (Con't)

Coefficients		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
		Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$	Coeff Value	Wald Stats $H_0:C_i=C_{i-1}$
C_{29}	$OrderSize_1$					-7.756**†						-2.273**†		-0.551†		-6.362**†	
C_{30}	$OrderSize_2$					-6.394**	0.4					-1.869**	0.3	-0.897**	0.5	-5.496**	0.2
C_{31}	$OrderSize_3$					-2.146**	8.7**					-0.777**	5.6	-0.504**	2.1	-1.915**	8.4**
C_{32}	$OrderSize_4$					0.164**	48.9**					0.104*	44.5**	0.266**	57.7**	0.155**	48.6**
C_{33}	$OrderSize_5$					4.466**	206.8**					1.481**	138.4**	1.226**	76.1**	3.955**	200.7**
C_{34}	$OrderSize_6$					0.883**	120.6**					0.540**	48.7**	0.470**	38.5**	0.865**	108.4**
C_{35}	$OrderSize_7$					2.339**	27.5**					1.864**	32.2**	1.754**	31.0**	2.297**	27.3**
C_{36}	$PriceInverse_1$							-0.324**†				-0.288**†		-0.283**†			
C_{37}	$PriceInverse_2$							-0.154**	2000.6**			-0.144**	883.7**	-0.140**	896.4**		
C_{38}	$PriceInverse_3$							-0.050**	7294.1**			-0.049**	4357.5**	-0.048**	3981.4**		
C_{39}	$PriceInverse_4$							0.062**	361.0**			0.066**	359.9**	0.067**	367.6**		
C_{40}	$PriceInverse_5$							0.053**	3.0			0.053**	4.7	0.052**	5.7		
C_{41}	$PriceInverse_6$							0.048**	52.4**			0.047**	49.2**	0.046**	54.2**		
C_{42}	$PriceInverse_7$							0.087**	110.1**			0.078**	60.8**	0.076**	53.0**		
C_{43}	$AvTrdVal_1$									0.604**†				0.263**†			
C_{44}	$AvTrdVal_2$									0.412**	695.5**			0.146**	207.1**		
C_{45}	$AvTrdVal_3$									0.183**	8060.4**			0.052**	892.2**		
C_{46}	$AvTrdVal_4$									0.016**	3194.6**			0.162**	85.3**		
C_{47}	$AvTrdVal_5$									-0.191**	4681.5**			-0.030**	267.1**		
C_{48}	$AvTrdVal_6$									-0.154**	487.2**			-0.035**	5.0		
C_{49}	$AvTrdVal_7$									-0.286**	242.8**			-0.100**	48.8**		
Overall Model Statistics																	
	Adjusted R-sq	0.554		0.547		0.531		0.795		0.560		0.798		0.800		0.549	
	No. of Obs	2,847,422		2,847,422		2,847,422		2,847,422		2,847,422		2,847,422		2,847,422		2,847,413	
	F-ratio	168173**		163240**		153458**		527020**		172827**		321344**		324735**		123710**	

Panel B: Implementation Shortfall

Coefficients		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
		Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}
C_1	Intercept_1	2.501**†		0.585**		1.243**†		1.001**†		2.066**†		1.214**†		0.589**†		0.584**	
C_2	Intercept_2	2.659**	14.7**	0.265**	204.1**	1.074**	528.2**	0.866**	140.4**	2.792**	260.2**	1.404**	8.7**	1.366**	121.2**	0.263**	206.5**
C_3	Intercept_3	1.960**	516.9**	-0.230**	754.1**	0.514**	9778.9**	0.284**	4005.9**	2.258**	227.5**	0.494**	303.5**	0.544**	194.1**	-0.233**	756.2**
C_4	Intercept_4	2.675**	328.0**	-0.059**	55.8**	0.750**	1044.8**	0.445**	67.7**	2.829**	165.3**	0.965**	18.9**	0.927**	10.7**	-0.079**	44.7**
C_5	Intercept_5	2.269**	123.6**	-0.194**	41.4**	0.653**	187.4**	0.372**	14.5**	2.651**	19.2**	0.525**	17.4**	0.679**	4.7*	-0.203**	33.9**
C_6	Intercept_6	2.334**	11.1**	0.138**	802.5**	0.760**	253.1**	0.538**	1771.3**	2.850**	75.0**	0.932**	225.2**	1.275**	295.6**	0.103**	581.9**
C_7	Intercept_7	3.723**	251.3**	0.659**	118.7**	1.474**	1256.2**	1.249**	1147.7**	4.484**	296.8**	1.650**	50.0**	2.100**	50.5**	0.525**	76.7**
C_8	Buy_1	-0.591**†		-0.606**†		-0.624**†		-0.608**†		-0.599**†		-0.602**†		-0.620**†		-0.605**†	
C_9	Buy_2	-0.308**	860.8**	-0.316**	911.0**	-0.331**	920.2**	-0.314**	956.4**	-0.303**	941.4**	-0.309**	934.7**	-0.309**	1039.6**	-0.318**	889.3**
C_{10}	Buy_3	-0.053**	1325.5**	-0.053**	1403.5**	-0.048**	1616.2**	-0.053**	1484.3**	-0.051**	1294.1**	-0.053**	1415.2**	-0.053**	1401.9**	-0.053**	1427.3**
C_{11}	Buy_4	0.508**	3631.0**	0.517**	3736.0**	0.527**	3826.7**	0.518**	3977.8**	0.514**	3674.8**	0.510**	3998.9**	0.512**	3998.5**	0.515**	3712.1**
C_{12}	Buy_5	-0.014**	3612.8**	-0.011**	3695.3**	-0.018**	3943.0**	0.015**	3684.0**	-0.013**	3689.4**	0.017**	3665.8**	0.017**	3668.3**	-0.007**	3616.4**
C_{13}	Buy_6	0.064**	341.9**	0.064**	315.3**	0.063**	352.9**	0.066**	231.9**	0.065**	352.7**	0.064**	201.7**	0.065**	204.5**	0.063**	272.6**
C_{14}	Buy_7	-0.157**	102.0**	-0.104**	57.5**	-0.161**	108.3**	-0.122**	83.9**	-0.198**	147.4**	-0.121**	88.9**	-0.136**	102.2**	-0.103**	60.8**
C_{15}	FirmSize_1	-0.124**†										-0.021**†					
C_{16}	FirmSize_2	-0.159**	79.2**									-0.055**	37.4**				
C_{17}	FirmSize_3	-0.145**	23.3**									-0.021**	57.1**				
C_{18}	FirmSize_4	-0.195**	173.9**									-0.054**	13.5**				
C_{19}	FirmSize_5	-0.161**	93.9**									-0.016**	18.8**				
C_{20}	FirmSize_6	-0.158**	3.6									-0.043**	133.7**				
C_{21}	FirmSize_7	-0.218**	51.0**									-0.053**	1.5				
C_{22}	Volatility_1			25.556**†												25.390**†	
C_{23}	Volatility_2			30.953**	38.5**											30.457**	33.7**
C_{24}	Volatility_3			28.179**	14.9**											28.187**	9.9**
C_{25}	Volatility_4			31.792**	15.5**											31.556**	13.5**
C_{26}	Volatility_5			32.717**	1.2											32.049**	0.3
C_{27}	Volatility_6			24.617**	273.0**											24.422**	243.4**
C_{28}	Volatility_7			36.908**	46.3**											35.580**	41.5**

Panel B: Implementation Shortfall (Con't)

Coefficients	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}	Coeff Value	Wald Stats H_0: C_i=C_{i-1}
C_{29} OrderSize$_1$					0.691**†						0.472**†		0.552**†		0.645**†	
C_{30} OrderSize$_2$					1.800**	14.9**					1.408**	18.2**	1.378**	13.7**	1.706**	15.4**
C_{31} OrderSize$_3$					0.295**	32.9**					0.234**	32.6**	0.229**	32.0**	0.296**	32.3**
C_{32} OrderSize$_4$					1.898**	62.1**					1.628**	67.1**	1.602**	66.1**	1.871**	61.7**
C_{33} OrderSize$_5$					4.472**	52.4**					1.488**	0.5	1.233**	3.7	3.961**	40.5**
C_{34} OrderSize$_6$					1.869**	41.8**					1.472**	0.0	1.338**	0.2	1.847**	31.4**
C_{35} OrderSize$_7$					2.894**	7.1**					2.434**	8.6**	2.323**	9.5**	2.853**	7.0**
C_{36} PriceInverse$_1$							0.065**†				0.064**†		0.067**			
C_{37} PriceInverse$_2$							0.040**	116.8**			0.039**	103.3**	0.039**	130.3**		
C_{38} PriceInverse$_3$							0.040**	0.3			0.039**	0.1	0.039**	0.0		
C_{39} PriceInverse$_4$							0.073**	57.7**			0.070**	41.3**	0.070**	42.5**		
C_{40} PriceInverse$_5$							0.053**	20.2**			0.053**	12.9**	0.053**	13.8**		
C_{41} PriceInverse$_6$							0.051**	9.9**			0.049**	25.9**	0.048**	36.1**		
C_{42} PriceInverse$_7$							0.086**	89.3**			0.078**	50.7**	0.075**	44.2**		
C_{43} AvTrdVal$_1$									-0.078**†				0.038**†			
C_{44} AvTrdVal$_2$									-0.166**	445.4**			-0.049**	214.5**		
C_{45} AvTrdVal$_3$									-0.168**	0.3			-0.025**	23.9**		
C_{46} AvTrdVal$_4$									-0.207**	90.5**			-0.050**	6.5*		
C_{47} AvTrdVal$_5$									-0.191**	16.7**			-0.030**	4.2*		
C_{48} AvTrdVal$_6$									-0.204**	36.5**			-0.074**	232.7**		
C_{49} AvTrdVal$_7$									-0.293**	96.2**			-0.097**	4.9*		
Overall Model Statistics																
Adjusted R-sq	0.017		0.016		0.012		0.101		0.018		0.102		0.102		0.017	
No. of Obs	5,110,703		5,110,703		5,110,646		5,110,703		5,110,703		5,110,632		5,110,632		5,110,639	
F-ratio	4186**		3956**		2942**		27238**		4350**		16528**		16539**		3183**	

ESSAY 2

THE ASYMMETRY OF PRICE BEHAVIOR AROUND BUY AND SELL TRADES: EMPIRICAL EVIDENCE ON THE STOCK EXCHANGE OF THAILAND

2.1 Introduction

The results of empirical studies (e.g., Chan and Lakonishok 1993, 1995; Escribano and Pascual 2006; Holthausen et al. 1987, 1990; Keim and Madhavan 1995, 1996, 1997; Kraus and Stoll 1972) that examine block and institutional equity trading show that order direction (e.g., buy or sell) influences the reaction of market participants. Buys are perceived asymmetrically from sells by market participants, and markets appear to react differently to buy and sell orders: Large buys induce increases in price, which then drop slightly or increase, whereas large sales induce drops in price, which almost fully recover.

Chan and Lakonishok (1993) suggest that information effects could be stronger for buys than for sales.[30] They point out that there are many liquidity-motivated reasons to sell a stock, while the choice of a certain stock to buy, out of the many alternatives available, is likely to convey positive private information. By contrast, Chiyachantana et al. (2004), Keim (2003), and Wagner and Edwards (1993) suggest that the total price impact of buys and sells is determined mainly by the underlying market conditions. Using total price impact as a measure of trading cost,[31] Chiyachantana et al. (2004) and Keim (2003) find empirical evidence supporting their hypothesis that buys (sells) are more expensive to execute than sells (buys) on bullish (bearish) markets. However, both studies did not relate market conditions to the asymmetry of permanent or temporary price impact of buys and sells.

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[30]The notion that buys are more informative than sales is important because it contradicts the assumption that the motivation for, and execution of, orders are symmetric between buys and sells, which is generally made by most asymmetric information trading models (e.g., Easley and O'Hara (1987; Glosten and Milgrom 1985; Kyle 1985). The exception is Burdett and O'Hara (1987), who argue that large buyers tend to be better informed than large sellers.

[31]Specifically, they use market-wide-return-adjusted total price impact as the main measure of trading cost in their study.

The study discussed in this article contributes to the existing literature by exploring the relationship between market conditions and the buy-sell asymmetry of permanent and temporary price impact.[32] That is, the present study argues that a contemporaneous market condition is the key factor behind the permanent and temporary price effect of buys and sales.

In addition, this study investigates whether and to what extent two alternative explanations about the buy-sell asymmetry of permanent price impact are valid. The first hypothesis suggests that buys are more informed than sells,[33] implying that buys will have a larger permanent price impact and smaller temporary price impact than sells, irrespective of market conditions. The empirical test of the first hypothesis conducted in this study is considered an out-of-sample test of the existing evidence on price effects of trades, which is primarily conducted in the United States or based on block and institutional trades. The second hypothesis is based on Saar's (2001) theoretical model. His model predicts that a stock's history of price performance drives the asymmetry of permanent price impact between buys and sales: the longer the stock price run-up, the less the permanent price impact asymmetry between buys and sales. The implication of his model, however, has not been formally tested. The empirical test on Saar's

[32] According to studies on block and institutional equity trades, the puzzling empirical evidence is the asymmetry of permanent and temporary price impact between buys and sales. For example, Holthausen et al. (1987) report that buys are associated with a price increase of 1.57%, which decreases by 0.03% (i.e., temporary price impact), leaving a permanent price impact of 1.54%. Sells are accompanied by a price drop of 2.48%, which increases by 1.30% (i.e., temporary price impact), leaving a permanent price impact of 1.18%. Keim and Madhavan (1996) report the asymmetry of temporary price impact between buyer-initiated and seller-initiated trades: That is, the stock prices of seller-initiated block trades reverse (i.e., go up) after trades by 2.84%, while the stock prices of buyer-initiated trades go up 0.15% after trades. However, there exists no significant asymmetry of permanent price impact: That is, they find that the permanent price impact for buyer-initiated block trades is approximately 1.60%, while for seller-initiated trades, it is approximately 1.50%.

[33] This notion is proposed and discussed by Burdett and O'Hara (1987), Chan and Lakonishok (1993), and Keim and Madhavan (1995, 1996).

prediction therefore highlights this study's contribution to the existing literature on the asymmetric price effect of buys and sales.

The present study makes several contributions to the literature on the price impact of trades. First, as shown earlier, this study relates market conditions to the buy-sell asymmetry of permanent and temporary price impact. In addition, it conducts empirical tests that examine two alternative hypotheses: (1) the notion that buys are more informative than sells and (2) the theoretical prediction that the buy-sell asymmetry of permanent price impact is related to a stock's history of price performance. Second, because a trade on SET can occur only at the quoted price, this study is very unlikely to encounter the problem of a misclassified trade (e.g., a buy classified as a sell and vice versa), which is frequently encountered by studies that use the NYSE Trade and Quotes (TAQ) database (see, for example, Bessembinder 2003a; Finucane 2000; Peterson and Sirri 2003).

Finally, this study conducts an out-of-sample test that examines previous empirical evidence about the price effects of trades, which is predominantly U.S.-based (i.e., markets with market makers) and based on block and institutional trades, and uses data from all trades on the Stock Exchange of Thailand (SET), an order-driven market. In addition, Thai data are used because this type of research has not been conducted on the Thai capital market, and the applicability of the U.S. results to a Thai market setting is debatable because of different trading settings.

There are two obvious differences in trading arrangements that can potentially have a major impact on liquidity and the price impact of trades. First, the major U.S. markets (i.e., NYSE, AMEX, and NASDAQ) have designated specialists/dealers who are obliged to supply liquidity, while on SET, liquidity is entirely supplied by natural buyers and sellers through limit orders (i.e., open limit order book system). Trading on SET is fully automated, and trades are placed through the Automatic Order Matching (AOM) system. Trading on U.S. exchanges is partially automated (e.g., on NYSE, there are both specialists and public limit orders placed through the SuperDOT system). Due to the existence of the designated specialists/dealers, liquidity is arguably higher on the U.S. markets than on SET. As a result, price impact of trades should be higher on SET than on the U.S. markets. Second, SET operates a truly centralized market system, whereas the U.S. markets are fragmented[34] (e.g., regional exchanges). According to Harris (2003), a consolidated market attracts liquidity due to order flow externality (i.e., the phenomenon where each trader who joins a market adds liquidity to the market, and the additional liquidity then attracts more traders, and therefore more additional liquidity). Therefore, liquidity (price impact of trades) should be higher (lower) in consolidated markets than in fragmented markets.

Our empirical results demonstrate that the price behavior associated with buys and sells is largely driven by market conditions, as hypothesized. There exists a buy-sell asymmetry for the two components of price impact (i.e., permanent and temporary price impact), and this asymmetry is influenced by market conditions. When the market is rising, a buyer-initiated trade incurs a higher permanent price impact (0.36% versus 0.07%) and lower temporary price impact (-0.01% versus 0.28%) than a seller-initiated trade. In a rising market, the price effects of buys are mostly permanent, while the price effects of sells are temporary. However, in a neutral market, there is less buy-sell asymmetry of price impact. The difference between permanent (temporary) price impact of buys and sells falls (rises) from

[34]The theoretical model by Yin (2005) suggests that spreads are smaller on centralized markets than on fragmented markets. Bennett and Wei (2006) report empirical evidence supporting the hypothesis that order fragmentation affects market quality (e.g., liquidity, price volatility, and price efficiency).

0.29% (-0.29%) in rising market to 0.20% (-0.20%) in a neutral market. In a falling market, the results of the buy-sell asymmetry of permanent and temporary price impact are inconsistent with the results of previous studies, but they support our hypotheses: That is, in a falling market, sells incur a larger permanent price impact than buys (0.56% versus 0.46%) and a smaller temporary price impact than buys (0.16% versus 0.25%), which indicates that the price effects of sells are relatively more permanent than the price effects of buys.

Even though the buy-sell asymmetry of permanent and temporary price impact is shown to be determined by market conditions, for very large trades (i.e., trade size larger than percentile 95), the results show that the permanent price impact of buys is always larger than the permanent price impact of sells, regardless of market conditions. These results are consistent with the alternative hypothesis that large buys are better informed than large sells. Specifically, the results show that for the largest trade group, the permanent price impact of buys still stays higher than the permanent price impact of sells for each of the three different market conditions, although the buy-sell asymmetry of a permanent price impact is reduced from 0.48% in a bull market to 0.14% in a bear market. Therefore, for very large trades, the buy-sell asymmetry of permanent price impact is consistent with the hypothesis that buys are more informed than sells.

The asymmetry of permanent price impact between buys and sells is further explored by examining the relationship between permanent price impact asymmetry and a stock's history of price performance, which is proxied using two measures: (1) the number of consecutive days a stock went up before the current day and (2) the magnitude of a stock's past returns. Our results do not support the relationship between a stock's history of price performance and the asymmetry of permanent price response to buys and sells. On the contrary, it seems that asymmetry is more or less influenced by contemporaneous market conditions, as predicted by our main hypothesis.

The remainder of this article is organized as follows: Section 2.2 provides a literature review and hypothesis development; the data, trade side classification, price impact calculation, and regression analyses are described in section 2.3; section 2.4 contains empirical results and robustness checks; and section 2.5 contains some conclusions.

2.2 Literature Review and Hypothesis Development

2.2.1 Three Explanations for the Price Impact of Large Trades

According to Chan and Lakonishok (1993) and Holthausen et al. (1987), price changes that accompany institutional and block trades can be explained in three ways: liquidity costs, inelastic demand curves, and information effects.

Liquidity costs, also known as price pressure, produce temporary price effects because it is difficult to find counterparties in a timely manner. In order to transact a large number of trades immediately, purchasers or sellers need to provide some compensation for the intermediary who provides liquidity. This compensation is usually a price concession. As a result, the liquidity cost explanation implies a quick recovery from a transacted price to a fair price before a trade.

Prices also change around large trades if there are no sufficiently perfect substitutes for a particular security. If buyers of a large number of shares face a supply curve not perfectly elastic, to induce sellers to sell more shares (than the equilibrium number of shares), they must offer a premium, or sweetener, to sellers.

Similarly, sellers of block trades must also offer a discount to potential buyers in order to induce them to buy and hold more shares. The imperfect substitution explanation implies permanent price impacts or slower price reversals subsequent to a trade compared to the speed of reversal proposed by the liquidity cost explanation.

Transactions can result in permanent price changes if they convey new information, which will subsequently be incorporated into prices. Informed trades could be implied by the identity of the traders conducting these transactions (e.g., insiders and high-ranked officers of companies). The trade size also can suggest the informativeness of a trade (Easley and O'Hara 1987).[35] The permanent price change with no price reversal, small price reversal, or price continuation supports the information effect explanation.

2.2.2 Buy-sell Asymmetry of Total, Permanent, and Temporary Price Impact

Holthausen et al. (1987, 1990), Keim and Madhavan (1996), and Kraus and Stoll (1972) report that price effects of block trades are predominantly (about 50%) temporary (i.e., supporting the liquidity cost hypothesis) for seller-initiated transactions and permanent (i.e., reflecting changes in the underlying value of a stock or information effect) for buyer-initiated transactions.

Like those who study block trades (e.g., Holthausen et al. 1987, 1990; Kraus and Stoll 1972), Chan and Lakonishok (1993) find that there is a buy-sell asymmetry for U.S. institutional equity trades.[36] The results of their study show that a buy order incurs a larger price impact than a sell order. In addition, after

[35]Koski and Michaely (2000) demonstrate that a trade's information effect on price is positively related to trade size.
[36]Bozcuk and Lasfer (2005), however, report that there is limited evidence to support the asymmetric price response hypothesis.

being executed, the buy order enjoys a price continuation, while the executed sell order faces substantial price reversals. Chan and Lakonishok (1993) propose that purchases may be more informative than sales.[37] The rationale behind this explanation is as follows: There are numerous liquidity reasons for sales. Furthermore, institutional investors can sell a particular stock out of the relatively limited number of stocks in their portfolio. Therefore, sales are not necessarily associated with negative information, but more likely to be liquidity motivated. On the contrary, there are fewer liquidity reasons to make purchases. Buys of any single stock out of a relatively large number of securities available on the market are likely to be driven by positive information.

Keim and Madhavan (1995) claim that buys are more information-motivated than sales. They find that institutional traders tend to spread buy orders over longer periods than similar sell orders (i.e., buys take longer to execute than similar-sized sells). The relative patience of buyers may reflect an underlying asymmetry in the price responses for buyer-initiated and seller-initiated trades (i.e., traders believe the price impact of buys are greater than the price impact of sells). The greater price responses to buys, in turn, imply that buys are probably more information-motivated than sells. Escribano and Pascual (2006) report that for the

[37] Actually, for the asymmetric price response of block buys and block sales, Chan and Lakonishok propose an explanation based on the common belief that block dealers are generally willing to fill their customers' large sales in exchange for price concessions, which will subsequently be reversed, while they are unwilling to take short positions against their clients' large purchases (see also Kraus and Stoll 1972). Therefore, it is less (more) likely that the block price for buyer-initiated (seller-initiated) trades includes a fee to block dealers in the form of a temporary price change. Instead, for buyer-initiated block trades, block dealers will be compensated in the form of a fee or commission. As a result, price changes after large sales (buys) tend to recover (stay the same or continue). Berkman et al. (2005) provide evidence that supports this idea. They show that, on stock index futures markets, where there is supposedly no additional cost for short selling, neither asymmetric permanent nor temporary price reaction to buys and sells is observed. Using data for stock-index and interest-rate futures traded on the Sydney Futures Exchange, Frino and Oetomo (2005) also show that price behavior after trades is more or less symmetrical between buys and sells.

11 most liquid NYSE-listed stocks in 1996 and 2000 buys are more informative than sells. Specifically, using an extended vector error correction model (VECM) for bid and ask quotes, they find that the bid and ask quotes do not adjust symmetrically after trades take place: The ask quote change as a result of a buyer-initiated trade is larger than the bid quote change as a result of a similar seller-initiated trade. Chan and Lakonishok (1995) and Keim and Madhavan (1997) study the execution cost of U.S. stock trades made by large investment management firms. Both studies find asymmetric price behavior associated with buys and sells: Buys are more expensive to trade than sells, even after controlling for several differences in order characteristics.

Saar (2001) proposes that stock price history is a determinant of buy-sell asymmetry: Block trades during periods of poor performance or little price appreciation (a price run-up) induce stronger (weaker or even negative) positive asymmetry.[38] Keim (2003) and Chiyachantana et al. (2004) argue that prevailing market conditions are the main driver behind previously documented buy-sell asymmetry of price impact and trading cost. Specifically, they suggest that buys (sales) in rising (falling) markets are more expensive (i.e., have a larger total price impact) than buys (sales) in falling (rising) markets because there is an excess demand (supply) for stock in bullish (bearish) markets. They claim this demand is the result of a combination of two factors: (1) increased demand for liquidity on the buy side as a result of positive feedback traders and (2) reduced supply because of unwillingness by the owners of recently appreciated stocks to sell their stocks in order to avoid realizing their capital gains. This line of reasoning is also applies to sells in falling markets.

[38]A positive (negative) asymmetry mean that buys (sales) have a larger permanent price impact than sales (buys).

The present study argues that a contemporaneous market condition is the key factor affecting permanent and temporary price impact. In other words, these two measures of the price impact (i.e., permanent and temporary price impact) of a trade depend on whether the trade supplies liquidity to the market or demands liquidity from the market. A buyer-initiated trade during a rising (falling) market is considered liquidity-demanding (liquidity-supplying). Likewise, a seller-initiated trade during a falling (rising) market is considered liquidity-demanding (liquidity-supplying). Therefore, a liquidity-demanding trade faces a higher price effect than a liquidity-supplying trade. This larger price effect is a result of larger information effects.[39] In a bullish (bearish) market, the buy (sell) trade carries more information than the sell (buy) trade. During a bullish (bearish) market, the proportion of informed trades in the pool of buys (sells) is higher than in the pool of sells (buys). Therefore, during a bullish (bearish) market, the major portion of the total price effect of buys (sells) becomes a permanent price effect (i.e., the larger proportion of the total price impact paid by the buyers [sellers] becomes permanent). Moreover, in an extremely bullish or bearish market, the information effects could even be more pronounced and greater in magnitude than the total price impact (i.e., the trading cost paid by a trade initiator). In this situation, the liquidity providers of the trade get picked off and regret trading. As a result, in a bullish (bearish) market, the buy (sell) incurs a larger permanent price impact than the sell (buy), and the temporary price impact, or the so-called price reversal, will be less or even negative

[39]For example, the standard asymmetric information models by Glosten and Milgrom (1985) and Easley and O'Hara (1987) predict that a portion of spread is due to adverse selection costs faced by liquidity suppliers. The prediction is also supported by empirical evidence from, for example, Glosten and Harris (1988) and Huang and Stoll (1997).

(i.e., price continuation) for the buy (sell). These arguments lead to the following hypotheses:

Hypothesis 1: During a rising (falling) market, buys (sells) incur a more permanent price impact but a less temporary price impact (i.e., price reversal) or even higher price continuation than sells (buys).

Hypothesis 1.1: Buys (sells) incur a more permanent price impact and a less temporary price impact (i.e., price reversal) or even higher price continuation during a rising (falling) market than during a falling (rising) market.

There are two alternative hypotheses to our main hypotheses. The first alternative hypothesis is the well-known belief that buys are more informationally motivated than sells (see, for example, Burdett and O'Hara 1987; Chan and Lakonishok 1993; Griffiths et al. 2001; Keim and Madhavan 1995, 1996). Therefore, according to this hypothesis, buys have a larger permanent price impact and less price reversal or even higher price continuation than sells, regardless of contemporaneous market conditions. This hypothesis is expected to be applicable to large trades. In general, large trades are more likely to be more informative than small trades because small trades are likely to be liquidity driven, speculative, or encouraged by brokers to accumulate stock positions for small price effects. On the other hand, large trades can result in a significant change in company ownership and probably provide information (Bozcuk and Lasfer 2005; Chan and Lakonishok 1993; Easley and O'Hara 1987; Glosten 1989; Keim and Madhavan 1996). Therefore, the asymmetric response of price effects to small buys and small sells is not anticipated. For large trades, however, the buy-sell asymmetry in information conveyed by trades is expected. The seller of a large sale may trade on negative information or for liquidity reasons. This liquidity motivation, however, is hard to defend for a large buyer (Burdett and O'Hara 1987; Chan and Lakonishok 1993). Even in bear markets, a block buy of a certain company (let alone a large buy in bull markets) is unlikely to be liquidity driven and more likely to be driven by favorable information. Large sells in a rising market, on the other hand, may not necessarily signal unfavorable news, but they could imply a large liquidation of stock positions at comparatively good prices. Therefore, for (very) large trades, the buy-sell asymmetry of price impact (i.e., permanent and temporary price impact) between buys and sells is expected.

The other alternative hypothesis is based on Saar's (2001) theoretical model. His model proposes that a stock's history of price performance is a determinant of a buy-sell asymmetry of permanent price impact: the longer the run-up in a stock's price, the less the asymmetry.[40] Specifically, large trades during periods of poor performance or little price appreciation induce stronger positive asymmetry (i.e., a permanent price impact of buys exceeds the permanent price impact of sales). On the other hand, trades occurring after a long period of price run-up will exhibit weaker or even negative asymmetry (i.e., permanent price impact of buys just exceeds or is lower than the permanent price impact of sells).

2.3 Data and Methodology

2.3.1 Data

In the present study, we use the transaction data for all securities traded on SET during three periods: March 29, 2000 to October 11, 2000, November 9, 2000 to July 31, 2001, and November 16, 2001 to June 13, 2002. The data were captured on-line in real time from Reuters and contain a time sequence of quote and trade

[40] *Asymmetry* is defined as "the permanent price impact of purchases minus the permanent price impact of sells."

records. Each trade record contains security name, date, time, and traded price, while each quote record contains the prevailing best bid and ask. The three distinct periods of our data are selected according to market conditions.[41] During the first period (i.e., March 29, 2000 to October 11, 2000), the SET index plummeted from 412 to 251, signifying a bearish market condition. In the second period (i.e., November 9, 2000 to July 31, 2001), the overall market return was -0.6%, indicating a neutral market condition. During the third period (i.e., November 16, 2001 to June 13, 2002), the SET index surged from 268 to 426 (equivalent to an increase of 46%), which indicates an extremely bullish market.

There are restrictions for stocks included in our analysis. First, an active trading day is defined as a day with a minimum of 20 trades, and a stock must have at least 130 active trading days in each of the three subperiods to be included in the analyses.[42] This resulted in 71 liquid stocks, with approximately 4.7 million trades. Second, trades that do not occur during normal trading hours (i.e., 10.00 AM to 12.30 PM, or 14.30 PM to 16.30 PM) are excluded from the analyses because these trades are transacted under a call auction system, which differs from the continuous trading system applied during normal trading hours. Third, trades that occur when a spread is negative are excluded from our analyses.

[41] The following criteria are used to select the three periods of study (i.e., bear, neutral, and bull periods). Based on the available data, we select three periods that correspond to a bearish, neutral, or bullish period, respectively. The magnitude and direction of the overall market index movement are used to classify such three market conditions. The characteristics of the three periods are presented in Table 2.1. Furthermore, in order to mitigate any potential biases, the absolute price change of the Thai index during bear and bull periods should be as close as possible, and the length of all three periods also should not be too different from each other. As a robustness check, we redo the analyses on the data with different periods. The results, not reported, are qualitatively the same as those on the original data.

[42] Ding and Charoenwong (2003) suggest that spreads of thinly traded futures contracts computed from days with trades are more informative than those computed from days without trades.

2.3.2 Methodology

2.3.2.1 Trade Side Classification

The present study uses Lee and Ready's (1991) quote-based rule to classify trades into buyer-initiated or seller-initiated trades. Trades completed at prices above (below) the prevailing quote midpoint are classified as buyer-initiated (seller-initiated). Trades executed at the prevailing quote midpoint are assigned by the tick test: That is, trades at a higher (lower) price compared to the price of the most recent trade are classified as buyer-initiated (seller-initiated) trades. In the TAQ database for U.S. stocks, trade reports are frequently delayed, and report times lag behind actual transaction times. Lee and Ready suggest a 5-second allowance so that trade times are deducted by 5 seconds before the trade and quote are matched. However, the present study does not use the 5-second delay in trade report times because the trade and quote time are usually perfectly matched on SET. In cases where there is a time difference between the quote and trade, the difference is always no more than 1 second.

2.3.2.2 Price Impact Calculation

The present study uses three empirical measures of price impact: total, permanent, and temporary price impact (see Chan and Lakonishok 1993; Kraus and Stoll 1972). The permanent price impact is considered an information effect, while the temporary price effect is considered a liquidity effect. The total price effect, regarded as the total price change around a trade, is the sum of the permanent and temporary price effects. Figure 2.1 illustrates the three measures of price impact of a trade.

The total price impact of a trade is measured as the percentage change from a true or unperturbed value of a security to the volume-weighted average executed prices of the shares filling the trade. The midpoint quotes at the trade time are used as a proxy of the true value of a security (see Boehmer 2005; Griffiths et al. 2000; Smith et al. 2001). The three measures of price impact (i.e., total, permanent, and temporary price impact[43]) are defined below.

The total price impact is mathematically defined as follows:

$TPI = \log(VWAP / mid - quote)$ for buyer-initiated trade

$TPI = \log(mid - quote / VWAP)$ for seller-initiated trade

where *TPI* refers to the total price impact of a trade, *VWAP* refers to the volume weighted average of the prices of the shares filling a trade, and *mid-quote* refers to the midpoint quote immediately before a trade.

The permanent price impact is mathematically defined as follows:

$PPI = \log(mid60 / mid - quote) - \log(SET60 / SET0)$ for buyer-initiated trade

$PPI = \log(mid - quote / mid60) - \log(SET0 / SET60)$ for seller-initiated trade

where *PPI* refers to the permanent price impact of a trade, *mid60* refers to the midpoint of a quote 60 minutes after a trade is executed,[44] and *mid-quote* refers to

[43]Our definitions of total, permanent, and temporary price impact correspond roughly to effective half spread, price impact, and realized half spread used by Bessembinder (2003b) and Bessembinder and Kaufman (1997a, 1997b).

[44]The present study also uses the midquote 30 minute after a trade as a measure of post-trade security value. The results for a 30-minute window are qualitatively the same as those for 60-minute window. From the existing literature, several proxies for post-trade value are used. For example, Kaniel and Liu (2006) use a 1-hour and 1-day window. Bessembinder and Kaufman (1997a, 1997b) and Bessembinder (2003b) use a 30-minute horizon. Venkataraman (2001) uses the first transaction price reported at least 30 minutes after a trade, and the midpoint of the first quotes reported after 12 noon on the next trading

the midpoint quote immediately before a trade. SET60 is the Stock Exchange of Thailand (SET) index value 60 minutes after a trade is executed. SET0 is the SET index value at the time of a trade. Consistent with prior studies (e.g., Bessembinder and Venkataraman 2004; Chiyachantana et al. 2004; Frino et al. 2005; Kraus and Stoll 1972), the permanent price effect is adjusted for overall market movements by subtracting the SET index return from the permanent price impact measure. A market-wide-adjusted permanent price impact can arguably be a more appropriate measure of information content conveyed by a trade because the effect of systematic price movement is removed.[45]

The temporary price impact is mathematically defined as follows:

$$TempPI = \log(VWAP / mid60) + \log(SET60 / SET0)$$ for buyer-initiated trade

$$TempPI = \log(mid60 / VWAP) + \log(SET0 / SET60)$$ for seller-initiated trade

where *TempPI* refers to the temporary price impact of a trade, *VWAP* refers to the volume weighted average of the prices of shares filling a trade, and *mid60* refers to the midpoint of a quote 60 minutes after a trade is executed. SET60 is the SET index value 60 minutes after a trade is executed. SET0 is the SET index value at the time of a trade. Like the permanent price impact measure, the temporary price effect is adjusted for overall market movements by adding the SET index return to the temporary price impact measure. A market-wide-adjusted temporary price

day. Bessembinder and Venkataraman (2004) use four different horizons: the first two horizons are the same as those of Venkataraman (2001), and the next two horizons are the midpoint of the closing quotes on the next (third) trading day after a trade. Huang and Stoll (1996) use the first trade prices 5 minutes and 30 minutes after an order is executed. Werner (2003) and Boehmer (2005) use the midpoint quote 5 minutes after a trade.

[45]Like the study by Keim and Madhavan (1996), the present study does not make any adjustment for an individual stock's market beta.

impact can arguably be a more appropriate measure of liquidity effect because the effect of systematic price movement is removed.

2.3.2.3 Regression Analysis

The three measures of price impact are, in fact, jointly determined by the variables affecting them. To disentangle the separate effects of all factors influencing price impact, the present study employs a regression model.[46]

Measures of market capitalization and trade size explain some of the variation in price impact[47]; however, previous studies (e.g., Harris 2003) suggest that the price impact of a trade is determined by two factors: depth and spread. Depth determines the cost for a trade with a relatively large size. On the other hand, the bid-ask spread is considered the minimum cost, irrespective of trade size. A lower limit on the bid-ask spread is determined by the minimum tick size, which suggests that the percentage spread is directly related to the inverse of a stock price (Harris 1994). Therefore, the inverse of a stock price is included in the regression model as one of the independent variables. In addition, spread increases in stock price volatility,[48] and a trading cost (e.g., posted spread) is positively related to stock volatility.[49] Therefore, stock price volatility is included in our regression equation. Trade size is a proxy for the amount of information conveyed by a trade, and as a result, larger trade sizes indicate higher permanent price impact (Easley and O'Hara 1987; Keim and Madhavan 1996). Therefore the dummy variables

[46]Note that in previous univariate analyses the results are based on both value-weighted and simple means; however, the regression model uses no weighting scheme.
[47]See Bessembinder (1997a, 1997b), Easley and O'Hara (1987), Griffiths et al. (2000), and Keim and Madhavan (1997, 1998).
[48]See, for example, Copeland and Galai (1983) and Ho and Stoll (1981).
[49]See Foucault (1999).

representing trade sizes are included in our regression equation. Specifically, the following cross-sectional regression is run:

$$PPI_i = \beta_0 + \beta_1 * buy0_i + \beta_2 * buy25_i + \beta_3 * buy50_i + \beta_4 * buy75_i + \beta_5 * buy90_i + \beta_6 * buy95_i + \beta_7 * buy99_i + \beta_8 * firmsize_i + \beta_9 * priceinv_i + \beta_{10} * volatility_i + \beta_{11} * tradesizepct0_i + \beta_{12} * tradesizepct25_i + \beta_{13} * tradesizepct50_i + \beta_{14} * tradesizepct75_i + \beta_{15} * tradesizepct90_i + \beta_{16} * tradesizepct95_i + \beta_{17} * tradesizepct99_i + \beta_{18} * dailyret_i + \varepsilon$$

subject to $\sum \beta_{11} + \beta_{12} + \beta_{13} + \beta_{14} + \beta_{15} + \beta_{16} + \beta_{17} = 0$

where $Buy0_i = Tradesizepct0_i * Buy_i$, $Buy25_i = Tradesizepct25_i * Buy_i$, $Buy50_i = Tradesizepct50_i * Buy_i$, $Buy75_i = Tradesizepct75_i * Buy_i$, $Buy90_i = Tradesizepct90_i * Buy_i$, $Buy95_i = Tradesizepct95_i * Buy_i$, $Buy99_i = Tradesizepct99_i * Buy_i$.

PPI_i is the permanent price impact, and it is defined as the natural logarithm of the ratio of the midquote 60 minutes before a trade to the midquote at the time of trade, adjusted by market-wide movement. The trade size categories are created in the following way: For each firm, all trades are ordered by their size in shares. Each firm's trades are partitioned into seven percentile categories: p0-p25, p25-p50, p50-p75, p75-p90, p90-p95, p95-p99, p99 up. Seven dummy variables are defined for each of those seven percentile categories. That is, $Tradesizepct0_i$, $Tradesizepct25_i$, $Tradesizepct50_i$, $Tradesizepct75_i$, $Tradesizepct90_i$, $Tradesizepct95_i$, and $Tradesizepct99_i$ are the dummy variables representing p0-p25, p25-p50, p50-p75, p75-p90, p90-p95, p95-p99, and p99 size categories respectively. Specifically, $Tradesizepct0_i$ is the dummy variable equal to 1 if the size percentile of the trade is between 0 and 25 and zero if otherwise. The remaining six dummy variables are defined similarly. Buy_i is the dummy variable equal to 1 if a trade is buyer-initiated. $Firmsize_i$ refers to the natural logarithm of market capitalization of a firm as of the beginning day of each of the three subperiods. $Priceinv_i$ represents 100 times the inverse of a stock price at the time of trade. $Volatility_i$ is the standard deviation of stock returns of each firm in each of the three subperiods. $Dailyret_i$ is the contemporaneous daily return on a stock.

For each of the two dependent variables (i.e., permanent price impact, and temporary price impact), the above regression equation is estimated separately for the three specified market conditions (e.g., bear, neutral, and bull markets). The regression equation is also run for all trades and separately for buys and sells.

2.4 Empirical Results

2.4.1 Descriptive Statistics of Trades

Table 2.1 provides descriptive statistics about the characteristics of trading in the sample of 71 stocks listed on SET during the three distinct periods described in the data section. As reported in Panel A, Table 2.1, our data include trades for 71 stocks across three periods. The number of trading days for Period 1 is roughly the same as for Period 3 (i.e., 133 versus 139 trading days), while Period 2 has the highest number of trading days (i.e., 177 trading days). Average market capitalization and volume-weighted trade price are highest in Period 1, lower in Period 2, and slightly higher in Period 3.[50] The movement from period to period in the values of average market capitalization and volume-weighted traded price is consistent with the market return and value-weighted 71-stock return.

The central difference between the three sample periods is market condition. The market return[51] in the first period is -49.8%. In the second period, market-wide performance is dormant, with a slightly negative market return. The market became bullish in the third period, with a market return of 46.3%. The value-weighted return of the 71 stocks analyzed in this study follows the market

[50]Average market capitalization is computed as of the first trading day of each period.
[51]Market return is measured by the buy and hold return on the SET index.

return trend but with more variability during Period 1 and Period 2, which suggests that these 71 stocks' beta is probably slightly larger than 1. Therefore, it is safe to assume that the market condition was bearish in Period 1, neutral in Period 2, and bullish in Period 3. With such stark differences in market conditions, a solid test about whether and to what extent market conditions influence the asymmetry of price impact between buys and sells can be reasonably performed.

Panel A, Table 2.1 shows that quoted and relative quoted spreads are relatively constant from Period 1 to Period 2; however, they are reduced by half in Period 3. For example, the quoted spread (relative quoted spread) is 0.400 baht[52] (1.449%) in Period 1, slightly drops to 0.314 baht (1.458%) in Period 2, and declines sharply to 0.188 baht (0.701%) in Period 3. The sharp drop in quoted and relative quoted spreads in Period 3 is a result of a new minimum tick size rule that was first applied in that period (i.e., on November 5, 2001).

Panel B, Table 2.1 illustrates the characteristics of all trades for the 71 stocks during the three periods. It also breaks down these characteristics into buyer-initiated and seller-initiated trades. First of all, the trading activity is sluggish in the down market, but livelier in the neutral market, and extremely dynamic in the rising market. As shown in Panel B, Table 2.1, the number of trades and daily number of trades, the baht volume of trades and daily baht volume of trades, and the number of shares traded and daily number of shares traded increase as the market becomes more bullish. In addition, average trade size in terms of the number of shares (as measured by average number of shares per trade or median number of shares per trade) and baht volume per trade is larger as the market becomes more bullish. This observation applies for buys and sells.

[52]At the time of this writing, the exchange rate was approximately 1US$:40 baht.

For each of the three periods, trading activity (as measured by daily number of trades, daily baht volume of trades, and daily number of shares traded) appears to be evenly split between buys and sells; however, seller-initiated trades appear to be larger in size than buyer-initiated trades. This observation is more pronounced during the bearish market: for example, in Period 1, the average number of shares per trade and the baht volume per trade for buyer-initiated trades are 9,547 shares and 141,154 baht, respectively, while the corresponding numbers for seller-initiated trades are 11,305 shares and 165,827 baht, respectively. The observation that sells are always larger in size than buys, regardless of market conditions, could be consistent with the idea that buys are more informative than sells and, therefore, more difficult to execute, which results in buys being broken up into smaller-sized trades (Chan and Lakonishok 1993; Keim and Madhavan 1995). Even though the fact that sells are larger in size than buys especially during the bear market, could be the driver behind the reversed buy-sell asymmetry of price impact (i.e., sell price impact is larger than buy price impact), the present study compares price impact of buys and sells while controlling for trade size differences by making buy-sell price impact comparisons for each of the trade size percentile categories.

The present study further investigates the trade characteristics of the 71 stocks partitioned by trade size (see Panel A, Table 2.2) and market capitalization (see Panel B, Table 2.2). In Panel A, the 71 stocks are divided into seven trade size categories for each period. The trade size categories are constructed in the following way. For each period and each firm, all trades are ordered by their size in shares. For each period, each firm's trades are divided into the following seven percentile categories: less than 25%, 25% to 50%, 50% to 75%, 75% to 90%, 90% to 95%, 95% to 99%, and larger than 99%. The share size cutoffs corresponding to each percentile are established based on each firm's trade size distribution in each period; therefore, the cutoffs vary in absolute share size across firms and periods. This trade size classification is used to define trade sizes for each firm relative to the order flow experience for the firm over each of the three periods. As expected, trade size, as measured by both average and median number of shares per trade and by baht volume per trade, increases with the trade size percentile. For example, in Period 1, the average number of shares per trade (baht volume per trade) is 935 shares (12,593 baht) for the less than 25% category and increases to 11,920 shares (176,965 baht) for the 75% to 90% category and 178,878 shares (2,388,763 baht) for the larger than 99% category. Consistent with the results shown in Panel B, Table 2.1, it is apparent that for any trade size category trade size in shares (as measured by average number of shares per trade or median number of shares per trade) increases as the market condition becomes more bullish. In addition, percentage of buys is usually higher in small trade size categories and lower in large trade size categories.[53] This appears to confirm that seller-initiated trades are generally larger in size than buyer-initiated trades (see Panel B, Table 2.1).

In Panel B, Table 2.2, the sample firms are divided equally into three groups based on market capitalization at the beginning of each period. As expected, the firm size distribution is skewed to the right because the average market capitalization of large firms is nearly eight times (30 times) as large as the average market capitalization of medium firms (small firms).

[53]Even though the percentage of buys in Period 2 and Period 3 becomes higher in the larger than 99% category, it simply reflects the fact that the degree to which sells are larger than buys is lower in neutral and bullish markets (i.e., Period 2 and Period 3), as shown in Panel B, Table 2.1. In addition, it may reflect the idea that large trades are informed and move the market; That is, large sells (i.e., sells in the larger than 99% category) move the market in Period 1 (i.e., falling market), and large buys (i.e., buys in the larger than 99% category) move the market in Period 3 (i.e., rising market).

During the bearish and neutral markets (i.e., Period 1 and Period 2), the number of trades increases with firm size; however, during the bullish market (i.e., Period 3), the number of trades is higher in smaller firms. These results suggest that during rising markets investors are more speculative and, therefore, active in small stocks; on the other hand, during falling markets, investors are conservative and, therefore, actively trade large-cap stocks. The value-weighted stock returns also support our assumption by showing that small stocks are riskier than large stocks (i.e., have more variability in returns). As expected, baht volume of trades increases with firm size across all periods. For example, in Period 2, the baht volume of trades (daily baht volume of trades) is 190,064 million baht (1,074 million baht) for the large firm group and 74,269 million baht (420 million baht) for the small firm group. Across all periods, there appears to be no apparent relationship between percentage of buys and firm size. Across all periods and firm sizes, the percentage of buys simply indicates the fact that sells are larger in size than buys, as also shown in Panel B, Table 2.1. For example, across all firm sizes during Period 1, buys are more frequent than sells (i.e., the percentages of buys in terms of number of trades are all greater than 50%), but buys account for less baht and share volume than sells (i.e., the percentages of buys in terms of baht volume of trades and number of shares traded are all less than 50%).[54] Across all periods, trade size (as measured by average and median number of shares per trade) typically decreases as firm size increases: For example, in Period 1, the average (median) number of shares per trade is 11,805 (5,000) shares for small firms, and it decreases to 8,949

[54]For Period 2 and Period 3, the percentage of buys in terms of number of trades is greater than 50%, and the percentage of buys in terms of baht volume of trades and number of shares traded is also greater than 50%. This most likely reflects the fact that the degree to which sells are larger in size than buys is lower as the market becomes more bullish (see Panel B, Table 2.1).

(2,000) shares for large firms. However, baht volume per trade increases monotonically with firm size. All of these results substantiate the fact that larger firms' stock prices are higher, which is indeed the case: Across all periods, the volume-weighted trade price increases as firm size increases.

2.4.2 The Relationships between the Price Impact of Buyer-Initiated and Seller-Initiated Trades and Market Conditions

Table 2.3 presents arithmetic mean results[55] for total, permanent, and temporary price impact classified by trade direction and trade size. Table 2.3 also shows the difference between the price impact of buys and the price impact of sells. Figure 2.2(A) illustrates the results for the buy-sell asymmetry of permanent price impact shown in Table 2.3, while Figure 2.2(B) illustrates the results for the buy-sell asymmetry of temporary price impact.

Table 2.3 shows that for all trade size categories prices for buyer-initiated trades are 0.71%, 0.72%, and 0.35% higher than the quote midpoint prevailing immediately before a trade during Period 1, Period 2, and Period 3, respectively. These price increases are consistent with the information effect and liquidity effect hypotheses. The initial price increase in Period 3 further increases by 0.01% after buys, leaving a permanent price impact of 0.36%, which supports the information effect hypothesis for buys. This is in line with previous findings that buys are associated with price continuation after purchases, implying that the information effect dominates the liquidity effect for buys. However, the initial price increases

[55]In order to make our results comparable to studies that examine the price impact of block and institutional equity trades (e.g., Chan and Lakonishok 1993, 1995), our study also computes the principal-weighted average of each price impact measure (not reported here). This procedure follows the norm in the investment industry and permits evaluation of the overall dollar amount of the price impact. However, the results from the principal-weighted mean procedure are qualitatively similar to the arithmetic mean results reported in this article.

of 0.71% (0.72%) in Period 1 (Period 2) are reversed by 0.25% (0.15%) after buys, making 0.46% (0.58%) of the total price increase permanent. Information and liquidity effects both appear to be valid. These results for Period 1 and Period 2 appear to slightly contradict previous findings about the price impact of block and institutional trades, but they support hypothesis 1.1 (i.e., buys have a higher permanent price impact and less temporary price impact during bull markets than during bear markets).

In Period 1, Period 2, and Period 3, there is an average drop in prices of 0.72%, 0.72%, and 0.35%, respectively, from the midpoint quote prevailing immediately before a seller-initiated trade to the executed selling price. These figures are nearly exactly the same in magnitude as those for buys (i.e., 0.71%, 0.72%, and 0.35%). The price drop of sells is also consistent with the information and liquidity effect hypotheses. The initial price drop in Period 3 encounters an almost complete reversal of 0.28% after sells, creating a permanent price effect of merely 0.07%. This is in line with previous findings that sells are associated with price drops and reversed fully after sales, which implies that the price effects of seller-initiated trades are primarily temporary. However, the initial price drops of 0.72% (0.72%) in Period 1 (Period 2) are reversed by 0.16% (0.34%) after sells take place, creating a permanent price effect of 0.56% (0.38%) for Period 1 (Period 2). Information and liquidity effects appear to be valid explanations for this price movement. Therefore, the results for Period 1 and Period 2 appear to moderately contradict previous findings that show the price effects of sells are caused mainly by liquidity effects, but again, they support hypothesis 1.1 (i.e., sells have higher permanent price impact and less temporary price impact during falling markets than during rising markets).

The results of the asymmetry of price impact in Table 2.3 show that the price behavior around buys and sells is largely driven by market conditions, as hypothesized. There exists a buy-sell asymmetry for the two components of price impact (i.e., permanent and temporary price impact), and asymmetry is influenced by market conditions. Figure 2.2(A) and Figure 2.2(B) illustrate the results shown in Table 2.3. Figure 2.2(A) and Figure 2.2(B) present the relationship, classified by trade size, between market conditions and the buy-sell asymmetry of permanent and temporary price impact, respectively. Consistent with hypothesis 1, when the market is bullish (i.e., Period 3), a buyer-initiated trade incurs a higher permanent price impact (0.36% versus 0.07%) and lower temporary price impact (-0.01% versus 0.28%) than a seller-initiated trade. In the bullish market, price effects of buys are principally permanent, while price effects of sells become temporary. This buy-sell asymmetry of price impact is illustrated by previous studies that examine institutional equity trades (e.g., Chan and Lakonishok 1993, 1995; Keim and Madhavan 1997) and block trades (e.g., Holthausen 1987, 1990; Keim and Madhavan 1996; Kraus and Stoll 1972). However, the situation changes when we move from bullish to bearish periods. In the neutral market (i.e., Period 2), the degree of buy-sell asymmetry of price impact lessens. The difference between permanent (temporary) price impact of buys and sells decreases (increases) from 0.29% (-0.29%) in the bullish market to 0.20% (-0.20) in the neutral market. In the bearish market (i.e., Period 1), the results of the buy-sell asymmetry of permanent and temporary price impact are inconsistent with the results of previous studies, but they support hypothesis 1. Evidently, the buy-sell asymmetry of price impact found in bullish market conditions reverses when the market is bearish. In the bearish market (i.e., Period 1), sells incur a larger permanent price impact than buys

(0.56% versus 0.46%) and a smaller temporary price impact than buys (0.16% versus 0.25%), which indicates that the price effects of sells are relatively more permanent than the price effects of buys. While there is a reverse in buy-sell asymmetry of total price impact (i.e., the total price impact of sells is higher than the total price impact of buys), which was discovered by Chiyachantana et al. (2004), the reverse in buy-sell asymmetry of permanent and temporary price impact has not been identified until the present study.[56] This discovery highlights the contribution made by this study.

From the results for a large-sized trade (e.g., trade size larger than 99%), one important implication is revealed. As discussed earlier, the buy-sell asymmetry of permanent and temporary price impact in Table 2.3 is influenced by market conditions; however, as shown on Figure 2.2(A), for larger trade size categories, it appears that the permanent price impact of buys is always larger than the permanent price impact of sells, regardless of market conditions. This is consistent with the alternative hypothesis that large buys are better informed than large sells. For example, for trades in the largest trade size category (i.e., larger than 99%), although the buy-sell asymmetry of permanent price impact is reduced from 0.48% in the bull market to 0.14% in the bear market, the permanent price impact of buys still stays higher than the permanent price impact of sells for each of the three different market conditions, which supports the hypothesis that buys are more informative than sells. These results are also found for trades in the 95% to 99% category. Therefore, for very large trades, the buy-sell asymmetry of permanent

[56]To the best of our knowledge, there has been no study that examines the relationship between market condition and the buy-sell asymmetry of permanent and temporary price impact.

price impact is consistent with the hypothesis that buys are more informed than sells.

Finally, Table 2.3 shows a preliminary relationship between trade size and price impact. The total and permanent price impact increases with trade size, while the temporary price effect decreases with trade size. If the total price impact is regarded as the implicit execution cost, these results suggest that larger trades are more expensive. This is consistent with the theoretical predictions by Easley and O'Hara (1987) and the empirical evidence about institutional equity trades discovered by Keim and Madhavan (1997, 1998). The larger permanent price impact and smaller temporary price impact of large trades indicate that large trades have more information than small trades (Easley and O'Hara 1987). For larger trades, the total price impact is primarily permanent; on the other hand, the price effect of smaller trades is driven more by liquidity than by information. This exploratory relationship is further investigated in the regression analysis in the Multivariate Analyses section.

2.4.3 Tests of the Alternative Theoretical Explanation about the Asymmetry of Permanent Price Impact between Buys and Sells

The previous section provides strong evidence that shows the influence of contemporaneous market conditions on the asymmetry of price impact between buys and sells. Saar (2001), however, develops a theoretical model to provide an alternative explanation about the asymmetric permanent price impact between buys and sells. His model associates a stock's history of price performance to permanent price impact asymmetry. Specifically, his model predicts a negative relationship between the buy-sell asymmetry of permanent price impact and q, where q

represents a stock's past price performance and is defined as the number of consecutive days in which the stock had good-information events up to yesterday.

Figure 2.3 illustrates the empirical and theoretical[57] relationship between permanent price impact asymmetry and q. Saar's theoretical prediction about the relationship between q and permanent price impact asymmetry is represented by *prediction*. The prediction suggests that asymmetry is highest when a stock did not go up yesterday (i.e., $q = 0$), and it becomes less as q becomes higher (i.e., a stock experienced a longer price run-up). The empirical evidence, represented by *empirical*, does not appear to support the prediction. The evidence shows that for most values of q the values of asymmetry are positive, except when $q = 4$ and 7 and the asymmetry values are negative. In short, empirically, it appears that a stock's history of price performance does not explain the asymmetry of permanent price response to buys and sells.

The present study also examines the empirical relationship between permanent price impact asymmetry and a stock's history of price appreciation by dividing the sample data shown on Figure 2.3 into three subsamples, which are based on three prevailing market conditions (i.e., bear, neutral, and bull market conditions). Figures 2.3(A), 2.3(B), and 2.3(C) illustrate the empirical relationship between buy-sell permanent price impact asymmetry and a stock's history of price run-up when market conditions are bearish, neutral, and bullish, respectively. Like the empirical results illustrated on Figure 2.3, the results for the three market conditions on Figure 2.3(A), 2.3(B), and 2.3(C) do not show any pattern similar to the pattern suggested by the prediction. On the contrary, asymmetry appears to support our hypotheses that permanent price impact asymmetry is driven by

[57]The theoretical relationship between permanent price impact asymmetry and q shown on Figure 2.3 is similar in shape to Figure 3 in Saar (2001, p. 1174).

concurrent market conditions: That is, asymmetry is not related to q values but to concurrent market conditions. During the bear market (see Figure 2.3[A]), asymmetry is mostly negative, irrespective of q values, while asymmetry during the neutral market (see Figure 2.3[B]) becomes more positive, regardless of q values. During the bullish market (see Figure 2.3[C]), almost all asymmetry is positive across a variety of q values. Therefore, the relationship between a stock's history of price performance and asymmetry of price response to buys and sells is not empirically supported. However, it appears that asymmetry is more or less influenced by contemporaneous market conditions, as indicated earlier by our hypotheses.

The asymmetry of permanent price impact between buyer-initiated trades and seller-initiated trades is further explored by examining the relationship between permanent price impact asymmetry and individual stock returns. In order to complement the earlier test on Saar's prediction, the present study examines the relationship between an individual stock's past returns and its current asymmetry of permanent price impact between buys and sells. Instead of measuring a stock's past performance by q, it is now measured by the magnitude of the stock's past returns. In addition to a stock's past return, the present study examines the relationship between a stock's current return and its current price impact asymmetry. This examination is used as a robustness check for our hypotheses and as a comparison benchmark for the asymmetry predictability of an individual stock's past return. These analyses allow for the possibility of some negative-return days/weeks/months within the broadly bullish period (i.e., Period 3), some positive-return days/weeks/months within the generally bearish period (i.e., Period 1), and both positive- and negative-return days/weeks/months within the neutral period (i.e., Period 2). These analyses also address any potential biases caused by the change in minimum tick size rule first applied during Period 3. Following Saar's prediction, the negative correlation between a stock's past return and the current buy-sell asymmetry of price effect is expected. On the other hand, according to hypothesis 1, a stock's current return should be positively correlated with the buy-sell asymmetry of permanent price impact. In addition, even within the generally bearish (bullish) market, the days/weeks/months with positive (negative) returns are still expected to be associated with positive (negative) permanent price impact asymmetry.

Table 2.4 shows the correlation values between individual stock conditions and permanent price impact. Across all periods, the correlation values between yesterday's stock returns and the permanent price impact of buys (sells) ranges from -0.01 to -0.05 (-0.05 to 0.01), while the correlation between yesterday's stock returns and permanent price impact asymmetry (i.e., permanent price impact of buys minus the permanent price impact of sells) is between -0.04 and 0.03. The results by day of the week also reveal a very low correlation between previous day return and permanent price impact measures. On the contrary, the correlation between contemporaneous stock return and permanent price impact is much stronger and has expected signs. Across all three market conditions, the correlation between current day return and price impact of buys is approximately 0.30, and the correlation between current day's stock return and price impact of sells is between -0.32 and -0.51. The relationship between permanent price impact asymmetry (i.e., buys – sells) and current day's stock return is also strong, with correlation values ranging from a significant 0.35 to 0.41 across all three market conditions. Once again, across day of the week, the correlation between current day return and permanent price impact clearly indicates a strong relationship with expected signs. Finally, the correlation results for week and month periods resemble the results for day period. Therefore, the results shown in Table 2.4 provide further support for hypothesis 1 and, at the same time, cast doubt on the explanation that a stock's history of price performance plays a role in determining the permanent price impact asymmetry between buys and sells.

2.4.4 Multivariate Analyses

Table 2.5 presents the coefficient estimates, along with adjusted R^2 values, of the regression equation outlined in the Regression Analysis section. Although the adjusted R^2 values are not high[58], almost all of the coefficient estimates are statistically significant and have predicted signs. Through regression analyses, the univariate results reported in Table 2.3 are mostly confirmed, even after controlling for several possible factors affecting permanent price impact.

The regression for all trades employs dummy variables for buys to examine the asymmetry of permanent price impact in the three distinct market conditions. Our hypotheses anticipate negative (positive) coefficient values for buy indicator variables in bearish (bullish) periods. In addition, the present study examines whether different trade sizes have different impacts on the asymmetry of permanent price impact by having a unique buy indicator variable for each of the seven trade size categories. Finally, for each period, the regression is run separately for buyer- and seller-initiated trades to examine the relationship between permanent price impact and contemporaneous individual stock returns; therefore, buy dummy

[58] The low R^2 values in the present study, however, are consistent with the findings of previous research (e.g., Chiyachantana et al 2004).

variables are dropped, but the current return of individual stock (i.e., *dailyreturn*) is added.

Consistent with the findings shown in Table 2.3, Table 2.5 shows that the dummy variables for buyer-initiated trades are negative (positive) during bearish (bullish) market conditions and are statistically significant at the 5% level and, more important, economically significant. Even after controlling for other factors affecting permanent price impact (i.e., firm size, stock price, stock price volatility, and trade size), buys have a lower permanent price impact than sells in the bear market (i.e., shown by the negative values of buy dummy variables) but have a higher permanent price impact than sells during the neutral and bull markets (i.e., shown by the positive values of buy dummy variables). For example, for trades with a size less than 25%, the permanent price impact of buys is 22bps (22bps) lower (higher) than equivalent sells during the bear (bull) market. Also consistent with the results in Table 2.3 and Figure 2.2(A), Table 2.5 shows that across all periods the values of buy dummy variables become larger from *buy0* to *buy99*: That is, as trade size increases, the buy-sell asymmetry of permanent price impact is larger (i.e., buys become more informed than sells for larger trades). For example, during the bear, neutral, and bull markets, the buy-sell asymmetry of permanent price impact increases monotonically from -0.22%, 0.15%, and 0.22%, respectively, in the smallest trade size category to 0.12%, 0.40%, and 0.48%, respectively, in the largest trade size category. In addition, after controlling for other factors (i.e., firm size, volatility, stock price, and trade size), buys in the largest trade size category always have a larger permanent price impact than sells in the same category, ranging from 12bps in the bear market to 48bps in the bull market. These results support the univariate results in Table 2.3, which show that large buys are more informed than large sells.

The coefficients of factors affecting permanent price impact are mostly as expected. Stocks of large firms have a lower permanent price impact because the asymmetric information problem is less prevalent in large firms than in small firms. Lower-priced stocks have a higher permanent price impact. Firms with volatile stock prices also have a higher permanent price impact. Finally, larger trades have a higher permanent impact on stock prices.

According to the separate regressions for buys and sells across all market conditions, the permanent price impact of buys (sells) has a positive (negative) relationship to contemporaneous stock return. Both relationships are statistically and economically significant. Across all three market conditions, on a day with stock rising (declining), the price impact of buys increases (decreases) while the price impact of sells decreases (increases) after firm size, stock price, stock price volatility, and trade size are controlled. A 1% increase (decrease) in stock returns increases (decreases) the permanent price impact of buys by 9.46, 11.71, and 13.35bps and lowers (increases) the permanent price impact of sells by 10.36, 12.73, and 13.10bps during Period 1, Period 2, and Period 3, respectively. The strong positive (negative) relationship between contemporaneous stock return and permanent price impact of buys (sells) obtained through regression analyses substantiates hypotheses 1 and 1.1.

2.4.5 Robustness Checks

The midpoint quote 30 minutes after a trade, instead of 60 minutes, is used as a post-trade benchmark price for calculating permanent and temporary price impact. For trade size classification, trade sizes are classified by absolute number of shares traded. Specifically, trades are divided into five categories: 0 to 1,000 shares, 1,000 to 5,000 shares, 5,000 to 10,000 shares, 10,000 to 50,000 shares, and more than 50,000 shares. The results for trade size classification are similar to the results for percentile classification. Previous studies (e.g., Holthausen et al. 1987, 1990) that examine the price impact of block trades classify trades according to the percentage of outstanding shares. Bozcuk and Lasfer (2005), however, find that trade size measured by the percentage of shares outstanding is not proper for testing the relationship between trade size and information conveyed by a trade. Under different robustness checks, our key findings are largely unchanged. For the sake of brevity, the results of these robustness checks are not reported.

2.5 Conclusion

Previous studies that examine institutional and block trades suggest that markets react differently to buys and sells. Price increases after large buys tend to remain the same or go up, while large sells are associated with price drops, which are then substantially reversed. In other words, price changes associated with buys (sells) are primarily permanent (temporary). The widely accepted explanation put forth in the literature is that buys are more informative than sells.

The present study proposes that market conditions drive the buy-sell asymmetry of permanent and temporary price impact of trades: That is, the two measures of price impact (i.e., permanent and temporary price impact) of a trade are determined by whether the trade supplies liquidity to the market or demands liquidity from the market. A trade in the same direction as (opposite direction to) the general market movement is considered a liquidity-demanding (liquidity-supplying) trade. A liquidity-demanding trade (i.e., buys in rising markets or sells in falling markets) has a larger permanent price impact and less temporary price impact than a liquidity-supplying trade (i.e., buys in falling markets or sells in rising markets). Specifically, the present study hypothesizes that during a bullish (bearish) market buys (sells) incur a more permanent price impact and less temporary price impact than sells (buys). The study provides empirical evidence that supports these hypotheses: That is, during the bullish market, the well-known asymmetry is detected; however, during the bearish market, asymmetry is reversed. This empirical result disproves the hypothesis that buys are more informative than sells because whether buys have a higher or lower permanent price impact than sells depends on contemporaneous market conditions. Our results are also confirmed after controlling for differences in stock characteristics and trade size through regression analyses.

For a very large-sized trade, even after controlling for differences in stock characteristics through regression analyses, the permanent price impact of buys is always larger than the permanent price impact of sells, regardless of market conditions, although the buy-sell asymmetry of permanent price impact is reduced from 0.48% in a bull market to 0.14% in a bear market. This finding is consistent with the well-known hypothesis that large buys are better informed than large sells.

The present study also hypothesizes that buys (sells) incur a more permanent price impact, with less temporary price impact during the bullish (bearish) market than during the bearish (bullish) market. Our empirical results support these hypotheses: That is, when the stock price rises (falls) by 1%, the permanent price impact of a buyer-initiated trade increases (decreases) by approximately 9.46 to 13.35bps, and the permanent price impact of a seller-initiated trade decreases (increases) by approximately 10.36 to 13.10bps.

The present study also conducts an empirical test that examines Saar's (2001) model. According to Saar's model, the permanent price impact asymmetry between buys and sells is influenced by a stock's history of price performance: the longer the run-up in a stock's price, the less the asymmetry (where asymmetry is defined as the permanent price impact of buys minus the permanent price impact of sells). The empirical results do not support the hypothesis that a stock's history of price performance drives the buy-sell asymmetry of permanent price impact. On the contrary, the results appear to confirm our hypothesis that buy-sell permanent price impact asymmetry is driven by contemporaneous market conditions.

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Table 2.1
Summary of Overall Trading Characteristics

This Table shows the characteristics of trading in 71 liquid stocks listed on the Stock Exchange of Thailand from March 2000 to June 2002. The sample period is divided into three market-wide conditions. Panel A presents overall statistics for each subsample. Panel B categorizes the overall sample characteristics at the trade level and includes the trade characteristics of buy and sell trades separately in addition to the combined statistics of all trades.

Panel A: Overall Sample Characteristics

	Period 1 (Mar 2000 - Oct 2000)	Period 2 (Nov 2000 - Jul 2001)	Period 3 (Nov 2001 - Jun 2002)
Number of stocks	71	71	71
Number of trading days (days)	133	177	139
Average market cap (million baht)	19,484	13,309	14,271
Volume-weighted trade price (baht)	14.72	12.64	12.51
Market return	-49.8%	-0.6%	46.3%
Value-weighted 71-stock return	-59.4%	-6.9%	44.7%
Quoted spread (baht)	0.400	0.314	0.188
Relative quoted spread	1.449%	1.458%	0.701%

Panel B: Trade Characteristics

	Period 1 (Mar 2000 - Oct 2000)			Period 2 (Nov 2000 - Jul 2001)			Period 3 (Nov 2001 - Jun 2002)		
	All	Buys	Sells	All	Buys	Sells	All	Buys	Sells
Number of trades	960,036	497,687	462,349	1,662,025	859,831	802,194	2,119,541	1,093,766	1,025,775
Daily number of trades	7,218	3,742	3,476	9,390	4,858	4,532	15,248	7,869	7,380
Baht volume of trades (million baht)	146,921	70,250	76,670	403,692	204,976	198,716	565,170	289,623	275,546
Daily baht volume of trades (million baht)	1,105	528	576	2,281	1,158	1,123	4,066	2,084	1,982
Number of shares traded (million shares)	9,978	4,751	5,227	31,944	16,197	15,746	45,195	23,070	22,125
Daily number of shares traded (million shares)	75	36	39	180	92	89	325	166	159
Average number of shares per trade	10,394	9,547	11,305	19,220	18,838	19,629	21,323	21,092	21,569
Median number of shares per trade	3,000	3,000	3,000	5,000	5,000	5,000	6,000	5,000	6,100
Baht volume per trade	153,037	141,154	165,827	242,892	238,391	247,715	266,647	264,794	268,623

Table 2.2
Summary of Trading Characteristics by Trade Size and Firm Size

This Table shows the characteristics of trading in 71 liquid stocks listed on the Stock Exchange of Thailand from March 2000 to June 2002. The sample period is divided into three market-wide conditions. The sample characteristics are divided by trade size in Panel A and by market capitalization in Panel B. The trade size categories are created in the following way: For each firm, all trades are ordered by their share sizes. Each firm's trades are then divided into seven percentile categories. The sample firms are divided equally into three groups that are based on market capitalization at the beginning of each period.

Panel A: Trade Characteristics Divided by Trade Size

	Period 1 (Mar 2000 - Oct 2000)						
	<25	25-50	50-75	75-90	90-95	95-99	>99
Average number of shares per trade	935	1,938	4,708	11,920	25,390	55,626	178,878
Median number of shares per trade	600	1,200	5,000	10,000	20,000	50,000	100,000
Median trade size corresponding to the percentile cutoffs	<1,000	1,000-3,000	3,000-10,000	10,000-20,000	20,000-45,500	45,500-100,000	>100,000
Baht volume per trade	12,593	29,435	80,463	176,965	392,286	790,633	2,388,763
Number of trades	161,731	260,686	245,044	177,791	57,262	46,203	11,319
Percentage of buys	53.7%	53.7%	52.3%	50.1%	47.6%	45.9%	44.8%
Daily number of trades	1,216	1,960	1,842	1,337	431	347	85
Baht volume of trades (million baht)	2,037	7,673	19,717	31,463	22,463	36,530	27,038
Percentage of buys	53.9%	53.3%	52.1%	49.5%	47.0%	45.2%	44.8%
Daily baht volume of trades (million baht)	15	58	148	237	169	275	203
Number of shares traded (million shares)	151	505	1,154	2,119	1,454	2,570	2,025
Percentage of buys	54.0%	52.9%	51.6%	49.3%	46.9%	45.2%	45.4%
Daily number of shares traded (million shares)	1.1	3.8	8.7	15.9	10.9	19.3	15.2

	Period 2 (Nov 2000 - Jul 2001)						
	<25	25-50	50-75	75-90	90-95	95-99	>99
Average number of shares per trade	1,276	2,848	8,152	20,475	51,402	112,236	355,957
Median number of shares per trade	1,000	2,000	6,700	13,000	48,500	88,000	210,000
Median trade size corresponding to the percentile cutoffs	<1,500	1,500-5,000	5,000-10,000	10,000-47,500	47,500-84,000	84,000-252,200	>252,200
Baht volume per trade	14,805	40,580	98,626	281,317	634,393	1,382,747	4,408,402
Number of trades	316,668	390,949	464,188	295,832	93,768	82,271	18,349
Percentage of buys	52.7%	52.0%	52.6%	50.3%	49.4%	49.2%	53.1%
Daily number of trades	1,789	2,209	2,623	1,671	530	465	104
Baht volume of trades (million baht)	4,688	15,865	45,781	83,222	59,486	113,760	80,890
Percentage of buys	52.2%	51.2%	52.1%	49.8%	49.3%	49.1%	54.4%
Daily baht volume of trades (million baht)	26	90	259	470	336	643	457
Number of shares traded (million shares)	404	1,113	3,784	6,057	4,820	9,234	6,531
Percentage of buys	52.3%	51.4%	52.3%	49.7%	49.2%	48.4%	54.9%
Daily number of shares traded (million shares)	2.3	6.3	21.4	34.2	27.2	52.2	36.9

	Period 3 (Nov 2001 - Jun 2002)						
	<25	25-50	50-75	75-90	90-95	95-99	>99
Average number of shares per trade	1,352	3,683	10,809	26,059	57,452	117,919	329,198
Median number of shares per trade	1,000	3,000	10,000	20,000	50,000	100,000	238,700
Median trade size corresponding to the percentile cutoffs	<2,000	2,000-6,000	6,000-20,000	20,000-50,000	50,000-100,000	100,000-229,000	>229,000
Baht volume per trade	15,727	51,546	122,160	341,256	701,919	1,473,766	4,181,313
Number of trades	420,961	505,170	573,820	372,306	123,312	99,559	24,413
Percentage of buys	53.9%	51.6%	51.7%	50.0%	49.5%	49.7%	55.4%
Daily number of trades	3,028	3,634	4,128	2,678	887	716	176
Baht volume of trades (million baht)	6,620	26,039	70,098	127,052	86,555	146,727	102,078
Percentage of buys	52.6%	50.7%	51.0%	49.4%	49.2%	49.8%	57.5%
Daily baht volume of trades (million baht)	48	187	504	914	623	1,056	734
Number of shares traded (million shares)	569	1,861	6,202	9,702	7,085	11,740	8,037
Percentage of buys	53.1%	52.0%	51.6%	49.5%	49.1%	49.0%	56.7%
Daily number of shares traded (million shares)	4.1	13.4	44.6	69.8	51.0	84.5	57.8

Panel B: Trade Characteristics Divided by Firm Size

	Period 1 (Mar 2000 - Oct 2000)			Period 2 (Nov 2000 - Jul 2001)			Period 3 (Nov 2001 - Jun 2002)		
	Small	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Average market cap (million baht)*	1,793	6,913	51,063	1,066	4,694	35,073	1,183	5,573	37,003
Volume-weighted trade price (baht)	7.2	11.4	24.3	7.9	10.4	20.8	10.1	11.8	16.6
Value-weighted stock return	-66.7%	-60.8%	-58.9%	-5.4%	3.3%	-8.4%	77.3%	61.1%	41.0%
Number of trades	240,031	328,547	391,458	466,811	592,052	603,162	776,640	709,550	633,351
Percentage of buys	50.5%	51.5%	52.9%	52.3%	51.3%	51.8%	52.5%	51.7%	50.4%
Daily number of trades	1,805	2,470	2,943	2,637	3,345	3,408	5,587	5,105	4,556
Baht volume of trades (million baht)	20,383	41,501	85,036	74,269	139,359	190,064	176,368	176,341	212,461
Percentage of buys	48.7%	47.8%	47.6%	52.4%	51.2%	49.8%	51.8%	51.5%	50.6%
Daily baht volume of trades (million baht)	153	312	639	420	787	1,074	1,269	1,269	1,528
Number of shares traded (million shares)	2,834	3,641	3,503	9,353	13,440	9,151	17,425	14,947	12,823
Percentage of buys	48.3%	47.8%	46.9%	51.4%	51.0%	49.6%	51.2%	51.1%	50.8%
Daily number of shares traded (million shares)	21	27	26	53	76	52	125	108	92
Average number of shares per trade	11,805	11,083	8,949	20,036	22,700	15,171	22,437	21,065	20,247
Median number of shares per trade	5,000	3,000	2,000	5,000	5,000	3,000	10,000	5,600	5,000
Baht volume per trade	84,918	126,318	217,230	159,098	235,383	315,113	227,091	248,525	335,455

* Market capitalization is computed as at the beginning of each period.

Table 2.3
Price Impact of Trades

This Table shows the arithmetic average values (in percent) of the three measures of price impact (i.e., total, permanent, and temporary price impact), classified by trade size, overall market conditions, and order direction (i.e., buys or sells). The sample comprises all trades in 71 liquid stocks listed on the Stock Exchange of Thailand from March 2000 to June 2002. The sample is divided into three market-wide conditions. The three measures of price impact for buyer-initiated trades are computed as follows: 1) *total price impact* is defined as "the natural logarithm of the ratio of the executed price to the midpoint quote at the time of trade," 2) *permanent price impact* is defined as "the natural logarithm of the ratio of the midquote 60 minutes before the trade to the midquote at the time of trade," and 3) *temporary price impact* is defined as "the natural logarithm of the ratio of the executed price to the midquote 60 minutes before the trade." The three components for seller-initiated trades are the minus of the above three expressions for buyer-initiated trades. Permanent and temporary price impact is adjusted by market-wide returns. The trade size categories are created in the following way: For each firm, all trades are ordered by their share size. Each firm's trades are then divided into seven percentile categories. All reported figures are statistically tested against zero value. Bold-faced type indicates significance at the 5% level.

Trade Size (Percentile)	Price Impact	Period 1 (Mar 2000 - Oct 2000)			Period 2 (Nov 2000 - Jul 2001)			Period 3 (Nov 2001 - Jun 2002)		
		Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells
All Trade Sizes	Total	**0.71**	**0.72**	**-0.01**	**0.72**	**0.72**	**0.00**	**0.35**	**0.35**	**0.00**
	Permanent	**0.46**	**0.56**	**-0.10**	**0.58**	**0.38**	**0.20**	**0.36**	**0.07**	**0.29**
	Temporary	**0.25**	**0.16**	**0.09**	**0.15**	**0.34**	**-0.20**	**-0.01**	**0.28**	**-0.29**
< 25	Total	**0.71**	**0.72**	**-0.01**	**0.75**	**0.74**	**0.01**	**0.35**	**0.35**	**0.00**
	Permanent	**0.31**	**0.54**	**-0.22**	**0.48**	**0.32**	**0.16**	**0.26**	**0.04**	**0.22**
	Temporary	**0.39**	**0.18**	**0.21**	**0.27**	**0.42**	**-0.15**	**0.09**	**0.31**	**-0.22**
25 - 50	Total	**0.70**	**0.71**	**-0.01**	**0.68**	**0.69**	0.00	**0.34**	**0.34**	**0.00**
	Permanent	**0.43**	**0.50**	**-0.07**	**0.51**	**0.33**	**0.18**	**0.31**	**0.04**	**0.27**
	Temporary	**0.27**	**0.21**	**0.06**	**0.17**	**0.35**	**-0.18**	**0.03**	**0.31**	**-0.28**
50 - 75	Total	**0.70**	**0.71**	**-0.01**	**0.75**	**0.75**	**0.00**	**0.35**	**0.35**	**0.00**
	Permanent	**0.45**	**0.55**	**-0.10**	**0.60**	**0.41**	**0.19**	**0.35**	**0.07**	**0.28**
	Temporary	**0.25**	**0.16**	**0.08**	**0.15**	**0.34**	**-0.19**	0.00	**0.28**	**-0.28**
75 - 90	Total	**0.73**	**0.75**	**-0.01**	**0.70**	**0.71**	**-0.01**	**0.34**	**0.35**	**0.00**
	Permanent	**0.55**	**0.60**	**-0.05**	**0.63**	**0.40**	**0.23**	**0.42**	**0.10**	**0.32**
	Temporary	**0.18**	**0.15**	**0.04**	**0.07**	**0.31**	**-0.24**	**-0.08**	**0.25**	**-0.33**
90 - 95	Total	**0.70**	**0.71**	**-0.01**	**0.74**	**0.74**	0.00	**0.35**	**0.36**	**-0.01**
	Permanent	**0.57**	**0.63**	**-0.06**	**0.70**	**0.43**	**0.27**	**0.50**	**0.11**	**0.38**
	Temporary	**0.14**	**0.09**	**0.05**	**0.04**	**0.31**	**-0.27**	**-0.15**	**0.24**	**-0.39**
95 - 99	Total	**0.75**	**0.75**	**-0.01**	**0.71**	**0.73**	**-0.02**	**0.36**	**0.36**	**-0.01**
	Permanent	**0.73**	**0.70**	0.02	**0.72**	**0.48**	**0.25**	**0.57**	**0.13**	**0.45**
	Temporary	0.03	**0.05**	-0.03	-0.02	**0.26**	**-0.27**	**-0.22**	**0.23**	**-0.45**
> 99	Total	**0.78**	**0.78**	0.00	**0.73**	**0.74**	-0.01	**0.39**	**0.39**	**-0.01**
	Permanent	**0.88**	**0.74**	**0.14**	**0.96**	**0.55**	**0.40**	**0.68**	**0.20**	**0.48**
	Temporary	**-0.10**	0.04	**-0.14**	**-0.22**	**0.19**	**-0.41**	**-0.30**	**0.20**	**-0.49**

Table 2.4
Correlations between Stock Conditions and Permanent Price Impact

This Table shows the correlation values between various types of individual stock returns and permanent price impact (of Buys, Sells, and Buys – Sells) of trades in 71 liquid stocks listed on the Stock Exchange of Thailand from March 2000 to June 2002. The sample is divided into three market-wide conditions. *Permanent price impact of buys (sells)* is defined as "the (negative) natural logarithm of the ratio of the midquote 60 minutes subsequent to the trade to the midquote at the time of trade, adjusted by market-wide returns." Buys (sells) refer to the permanent price impact of buyer-initiated (seller-initiated) trades. Buys – Sells (e.g., buys minus sells) is the difference between the permanent price impact of buyer-initiated trade and the permanent price impact of seller-initiated trade.

Return	Period 1 (Mar 2000 - Oct 2000)			Period 2 (Nov 2000 - Jul 2001)			Period 3 (Nov 2001 - Jun 2002)		
	Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells
Previous day return	-0.01	-0.05	0.03	-0.05	0.01	-0.04	-0.01	-0.02	0.00
- Monday	-0.07	0.00	-0.04	-0.10	0.06	-0.10	-0.03	0.01	-0.02
- Tuesday	-0.04	-0.03	-0.01	-0.01	-0.05	0.02	-0.03	0.00	-0.02
- Wednesday	0.03	-0.05	0.05	-0.01	0.00	-0.01	0.07	-0.09	0.08
- Thursday	0.05	-0.11	0.09	-0.10	0.06	-0.11	-0.03	0.00	-0.01
- Friday	-0.01	-0.08	0.04	-0.03	-0.01	-0.01	0.03	-0.06	0.05
Current day return	0.29	-0.32	0.35	0.32	-0.33	0.41	0.31	-0.51	0.40
- Monday	0.21	-0.36	0.32	0.28	-0.26	0.35	0.18	-0.37	0.24
- Tuesday	0.26	-0.22	0.27	0.35	-0.33	0.43	0.26	-0.43	0.34
- Wednesday	0.28	-0.24	0.29	0.27	-0.26	0.34	0.53	-0.61	0.59
- Thursday	0.41	-0.46	0.48	0.34	-0.40	0.47	0.57	-0.64	0.63
- Friday	0.36	-0.40	0.45	0.38	-0.39	0.46	0.61	-0.63	0.65
Previous week return	-0.13	0.00	-0.08	-0.07	0.00	-0.05	-0.04	0.05	-0.05
Current week return	0.30	-0.41	0.43	0.32	-0.36	0.47	0.48	-0.67	0.60
Previous month return	-0.17	0.08	-0.18	-0.04	-0.03	-0.01	-0.03	0.00	-0.02
Current month return	0.20	-0.44	0.41	0.25	-0.29	0.48	0.55	-0.67	0.64

Table 2.5
Regression Analysis of Permanent Price Impact

This Table shows the coefficient estimates (multiplied by 100) of a regression analysis of the permanent price impact of trades in 71 liquid stocks listed on the Stock Exchange of Thailand from March 2000 to June 2002. The sample is divided into three market-wide conditions. The regression equation is as follows:

$$PPI_i = \beta_0 + \beta_1 * buy0_i + \beta_2 * buy25_i + \beta_3 * buy50_i + \beta_4 * buy75_i + \beta_5 * buy90_i + \beta_6 * buy95_i + \beta_7 * buy99_i + \beta_8 * firmsize_i + \beta_9 * priceinv_i + \beta_{10} * volatility_i + \beta_{11} * tradesizepct0_i + \beta_{12} * tradesizepct25_i + \beta_{13} * tradesizepct50_i + \beta_{14} * tradesizepct75_i + \beta_{15} * tradesizepct90_i + \beta_{16} * tradesizepct95_i + \beta_{17} * tradesizepct99_i + \beta_{18} * dailyret_i + \varepsilon$$

subject to $\sum \beta_{11} + \beta_{12} + \beta_{13} + \beta_{14} + \beta_{15} + \beta_{16} + \beta_{17} = 0$

where $Buy0_i = Tradesizepct0_i * Buy_i$, $Buy25_i = Tradesizepct25_i * Buy_i$, $Buy50_i = Tradesizepct50_i * Buy_i$, $Buy75_i = Tradesizepct75_i * Buy_i$, $Buy90_i = Tradesizepct90_i * Buy_i$, $Buy95_i = Tradesizepct95_i * Buy_i$, $Buy99_i = Tradesizepct99_i * Buy_i$.

PPI_i is the permanent price impact, defined as the natural logarithm of the ratio of the midquote 60 minutes before the trade to the midquote at the time of trade, adjusted by market-wide movement. The trade size categories are created in the following way: For each firm, all trades are ordered by their share size. Each firm's trades are then divided into seven percentile categories. $Tradesizepct0_i$ is the dummy variable equal to 1 if the size percentile of the trade is between 0 and 25. $Tradesizepct25_i$ is the dummy variable equal to 1 if the size percentile of the trade is between 25 and 50. $Tradesizepct50_i$ is the dummy variable equal to 1 if the size percentile of the trade is between 50 and 75. $Tradesizepct75_i$ is the dummy variable equal to 1 if the size percentile of the trade is between 75 and 90. $Tradesizepct90_i$ is the dummy variable equal to 1 if the size percentile of the trade is between 90 and 95. $Tradesizepct95_i$ is the dummy variable equal to 1 if the size percentile of the trade is between 95 and 99. $Tradesizepct99_i$ is the dummy variable equal to 1 if the size percentile of the trade is larger than 99. Buy_i is the dummy variable equal to 1 if buyer-initiated trade. $Firmsize_i$ refers to the natural logarithm of market capitalization of the firm. $Priceinv_i$ represents the inverse of stock price at the time of trade. $Volatility_i$ is the standard deviation of stock returns. $Dailyret_i$ is the contemporaneous daily return on the stock. Bold-faced type indicates significance at 5% level.

Independent Variables	Period 1 (Mar 2000 - Oct 2000)			Period 2 (Nov 2000 - Jul 2001)			Period 3 (Nov 2001 - Jun 2002)		
	All	Buys	Sells	All	Buys	Sells	All	Buys	Sells
intercept	**0.65**	**-0.56**	**1.49**	**0.49**	0.07	**0.67**	**0.07**	**-0.74**	**0.90**
buy0	**-0.22**			**0.15**			**0.22**		
buy25	**-0.06**			**0.18**			**0.27**		
buy50	**-0.09**			**0.18**			**0.28**		
buy75	**-0.05**			**0.23**			**0.33**		
buy90	**-0.06**			**0.26**			**0.38**		
buy95	0.01			**0.25**			**0.45**		
buy99	**0.12**			**0.40**			**0.48**		
firmsize	**-0.02**	**0.03**	**-0.05**	**-0.02**	**0.01**	**-0.02**	**0.00**	**0.04**	**-0.02**
priceinv	**0.02**	**0.03**	**0.01**	**0.03**	**0.03**	**0.03**	**0.00**	**0.00**	**0.00**
volatility	**0.23**	**0.26**	**0.14**	0.03	**-0.07**	**0.17**	**-0.14**	0.03	**-0.30**
tradesizepct0	**-0.08**	**-0.11**	-0.01	**-0.11**	**-0.04**	**-0.09**	**-0.06**	**-0.03**	**-0.05**
tradesizepct25	**-0.09**	0.01	-0.01	**-0.05**	**0.03**	**-0.03**	**-0.06**	**0.02**	**-0.04**
tradesizepct50	**-0.05**	-0.02	-0.01	**-0.04**	-0.01	**-0.03**	**-0.03**	**0.01**	**-0.03**
tradesizepct75	-0.02	-0.01	0.00	0.00	**0.03**	-0.01	0.00	**0.02**	**-0.01**
tradesizepct90	0.03	0.01	0.00	0.00	-0.02	-0.01	**0.02**	0.01	0.01
tradesizepct95	**0.08**	**0.05**	0.02	**0.05**	**-0.03**	**0.05**	**0.03**	0.01	**0.03**
tradesizepct99	**0.13**	0.06	0.01	**0.14**	**0.04**	**0.11**	**0.10**	-0.02	**0.09**
dailyreturn		**9.46**	**-10.36**		**11.71**	**-12.73**		**13.35**	**-13.10**
No. of obs	865,591	449,618	415,973	1,548,131	804,348	743,783	1,978,780	1,024,852	953,928
Adj R^2	0.011	0.064	0.068	0.024	0.117	0.131	0.009	0.112	0.125

Figure 2.1
Total, Permanent, and Temporary Price Impact of a Trade

This Figure illustrates the three empirical measures of price effects of a trade. The security value immediately before the trades is P_0 at time t_0. A buyer-initiated trade is executed at price P_1 at time t_1, after which the price reverses to P_2 at time t_2. Therefore, permanent price change is the percentage price change from P_0 to P_2, while the temporary component of price change is the percentage price change from P_1 to P_2. Total price effect is the sum of these two components of price changes. The three measures of price impact are similarly interpreted for a seller-initiated trade.

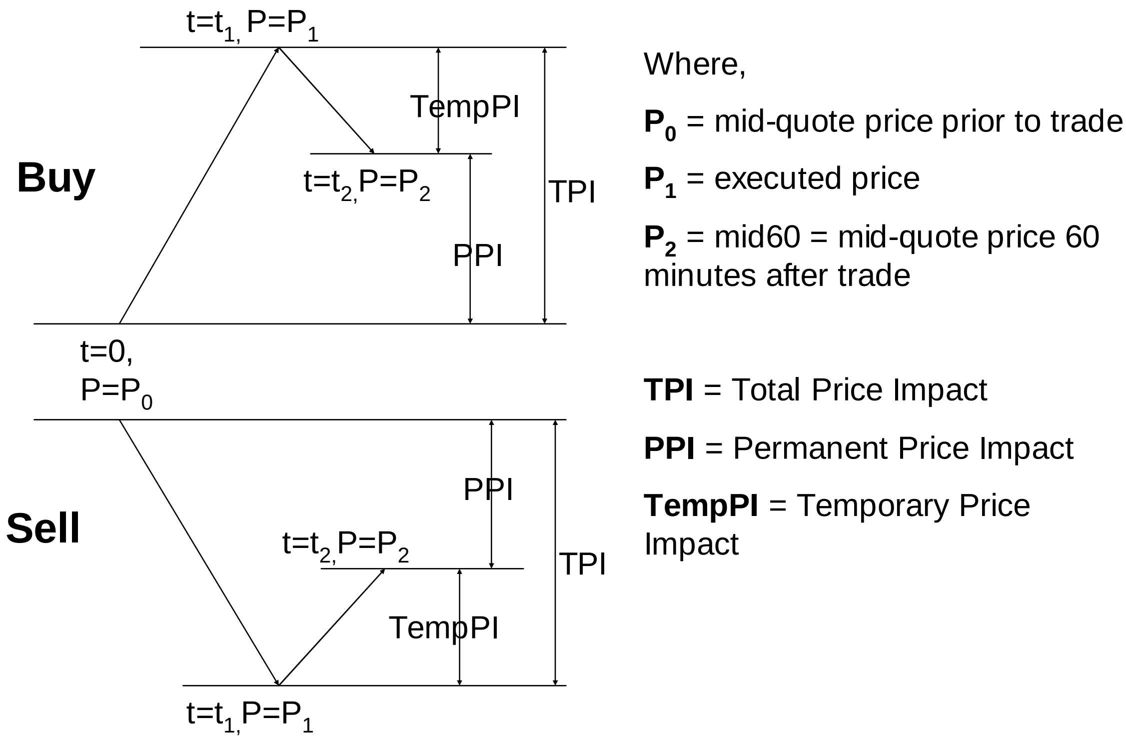


Figure 2.2(A)
Permanent Price Impact Asymmetry and Market Conditions across Trade Sizes

This Figure illustrates the arithmetic average permanent price impact asymmetry (i.e., defined by the difference between the permanent price impact of buys minus the permanent price impact of sells) for each market condition and trade size.

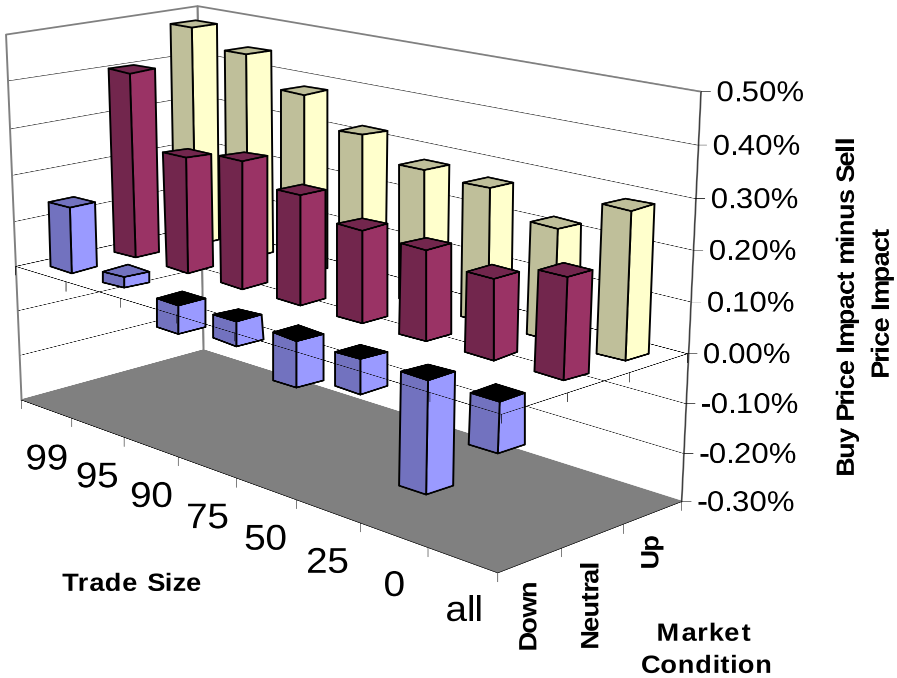


Figure 2.2(B)
Temporary Price Impact Asymmetry and Market Conditions across Trade Sizes

This Figure illustrates the arithmetic average temporary price impact asymmetry (i.e., defined by the difference between the temporary price impact of buys minus the temporary price impact of sells) for each market condition and trade size.

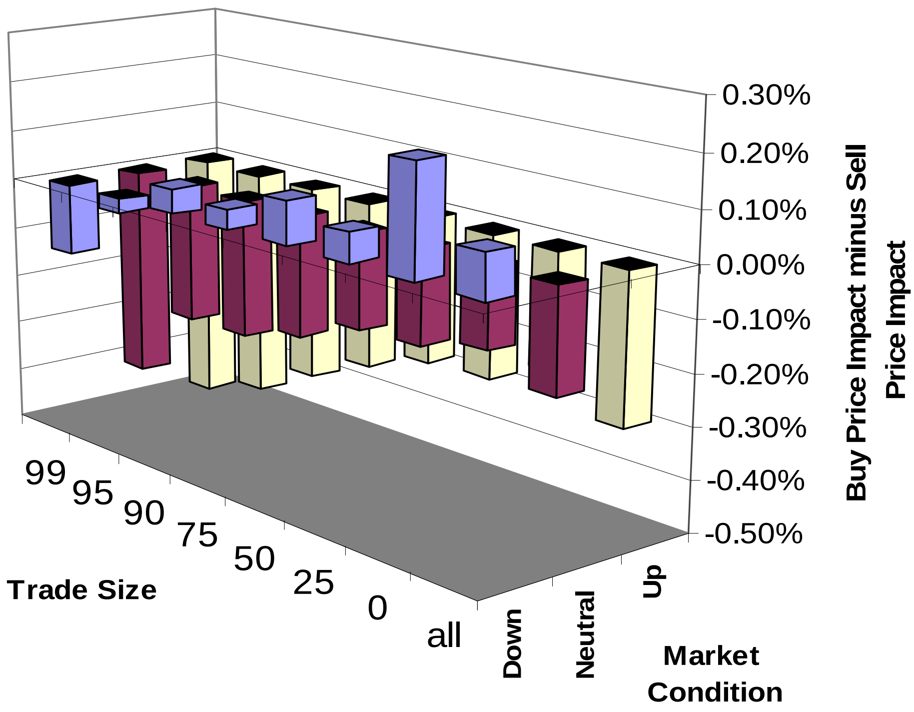


Figure 2.3
Permanent Price Impact Asymmetry and the Number of Consecutive Days in Which the Stock Goes Up

This Figure illustrates the empirical evidence (i.e., "Empirical") and the theoretical prediction (i.e., "Prediction") about the relationship between permanent price impact asymmetry (i.e., the difference between the permanent price impact of buys minus the permanent price impact of sells) and the number of consecutive days in which the stock goes up.

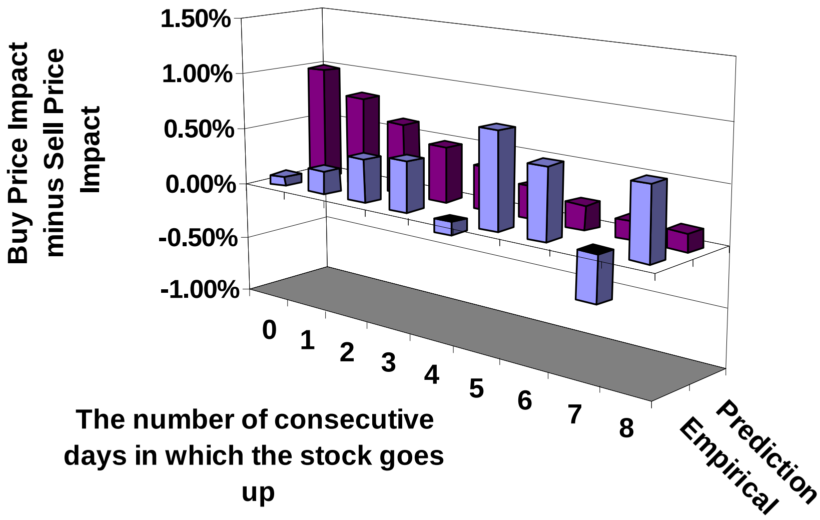


Figure 2.3(A)
Permanent Price Impact Asymmetry and the Number of Consecutive Days in Which the Stock Goes Up during the Bear Market

This Figure illustrates the empirical evidence (i.e., "Empirical") and the theoretical prediction (i.e., "Prediction") about the relationship between permanent price impact asymmetry (i.e., the difference between the permanent price impact of buys minus the permanent price impact of sells) and the number of consecutive days in which the stock goes up. The empirical evidence is for the bear market.

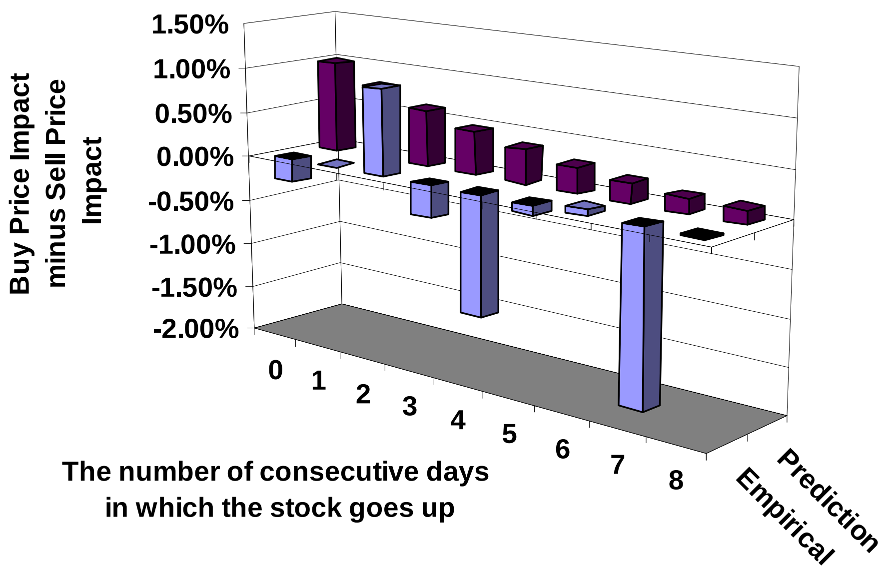


Figure 2.3(B)
Permanent Price Impact Asymmetry and the Number of Consecutive Days in Which the Stock Goes Up during the Neutral Market

This Figure illustrates the empirical evidence (i.e., "Empirical") and the theoretical prediction (i.e., "Prediction") about the relationship between permanent price impact asymmetry (i.e., the difference between the permanent price impact of buys minus the permanent price impact of sells) and the number of consecutive days in which the stock goes up. The empirical evidence is for the neutral market.

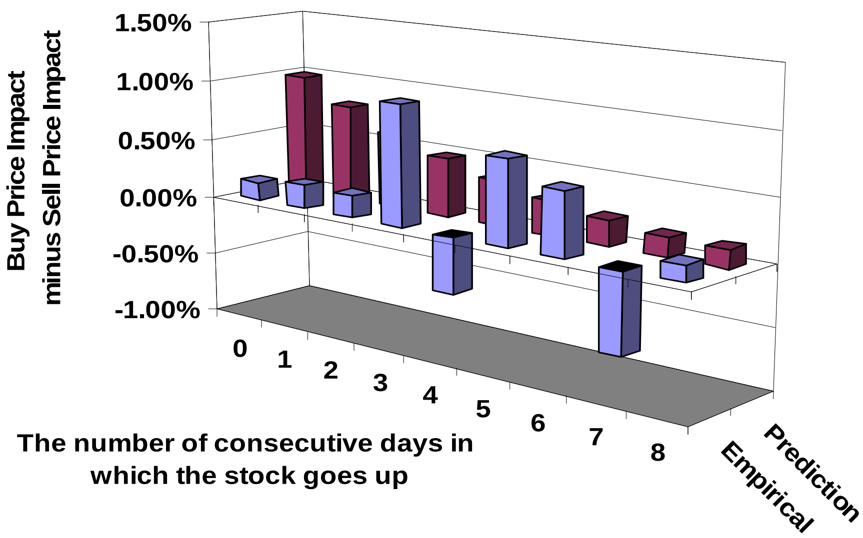
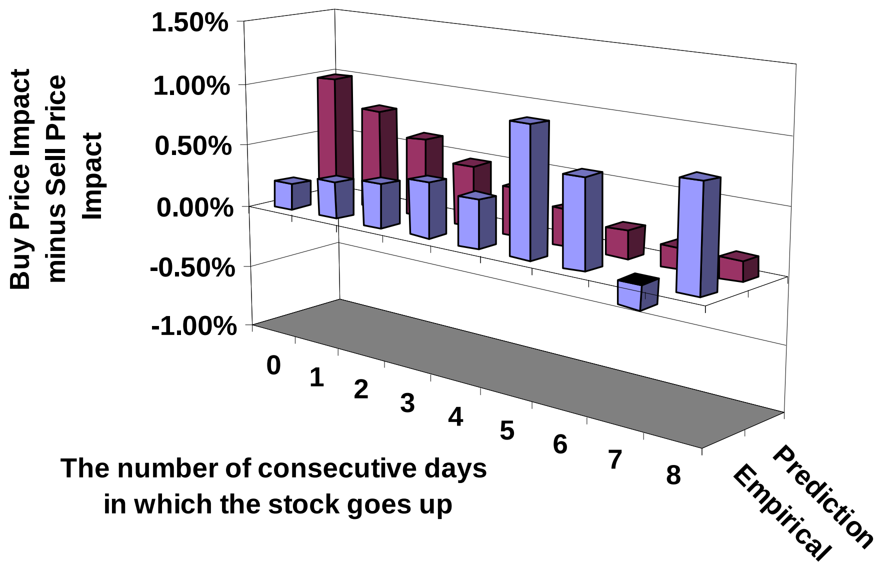


Figure 2.3(C)
Permanent Price Impact Asymmetry and the Number of Consecutive Days in Which the Stock Goes Up during the Bull Market

This Figure illustrates the empirical evidence (i.e., "Empirical") and the theoretical prediction (i.e., "Prediction") about the relationship between permanent price impact asymmetry (i.e., the difference between the permanent price impact of buys minus the permanent price impact of sells) and the number of consecutive days in which the stock goes up. The empirical evidence is for the bull market.



ESSAY 3

WHICH TRADE SIZES MOVE STOCK PRICES ON THE STOCK EXCHANGE OF THAILAND?

3.1 Introduction

Researchers (e.g., Kyle 1985) who examine informed trading suggest that profit-maximizing informed investors attempt to hide their trades by breaking up large trades into smaller trades and executing them over time in order to protect their valuable private information.[59] Admati and Pfleiderer (1988) suggest that informed traders camouflage their information by trading during high volume periods. Barclay and Warner (1993) propose the stealth trading hypothesis and argue that informed traders who want to avoid detection will break up their trades into several medium-sized trades because small-sized trades increase the likelihood that their private information will be revealed too quickly, and large-sized trades may have an excessively large price impact. The empirical evidence from NYSE (Anand and Chakravarty 2006; Anand et al. 2005; Barclay and Warner 1993; Chakravarty 2001) supports the stealth trading hypothesis.

However, studies on stealth trading focus totally on the U.S. markets (e.g., NYSE). No studies so far have been conducted on other markets (e.g., a pure limit order driven market). Studies on other markets are needed because several studies (e.g., Boehmer 2005; Garfinkel and Nimalendran 2002; Grammig et al 2001; Heidle and Huang 2002; Huang and Stoll 1996; Lee and Yi 2001) have shown that the presence of market makers has significant impact on the choice of trade sizes by informed traders. As a result, the applicability of stealth trading studies in the U.S. markets to other markets (e.g., a pure limit order market) is quite questionable. The present study is intended to fill such gap by examining informed traders' trade size choices in a pure limit order market (i.e., a market without market

[59]Keim and Madhavan (1995) empirically examine U.S. institutional equity trades and find that larger orders are usually spread over a longer period and associated with longer trading durations.

intermediaries). Specifically, this study empirically reexamines the stealth trading hypothesis (Barclay and Warner 1993) in a pure limit order market. Our central hypothesis predicts that in a pure limit order market informed traders concentrate their trades in medium-to-large sizes because there are no market makers who are able to recognize informed traders. This hypothesis is based on research (e.g., Boehmer 2005; Huang and Stoll 1996; Lee and Yi 2001) conducted on the Chicago Board Options Exchange (CBOE), New York Stock Exchange, (NYSE), and National Association of Securities Dealers Automated Quotations (NASDAQ) that documents market makers' ability to identify informed traders. These studies suggest that market structures influence how informed investors behave in order to hide their private information. Our empirical tests are based on 73 stocks listed on the Stock Exchange of Thailand (SET). There are no market makers operating on SET, and as a result, it provides a natural setting for examining how informed traders hide their trades in a pure limit order market and comparing this behavior to strategies used by informed traders on markets with market makers.

The present study's empirical results support our main hypothesis: That is, trades in the top quartile size (i.e., larger than percentile 75) collectively play a disproportionately large role in the cumulative price change and the cumulative quote change (i.e., they account for 168.4% [143.1%] of the cumulative stock price [quote] change compared to 28.3% of the total number of transactions and 80.8% of the total volume). Without market makers who are able to screen out informed trades, informed traders on SET use relatively large trades. This situation contrasts with the results of studies conducted on NYSE (e.g., Barclay and Warner 1993; Chakravarty 2001) that show informed traders use trades in percentile 40 to percentile 95 size group.

In addition, the present study examines informed traders' order-breakup strategies under different market conditions. Trading volume and liquidity are different under different market conditions (i.e., rising or falling markets); therefore, informed traders may adopt different strategies (e.g., trade sizes) in order to hide their trades under different liquidity conditions (Campbell et al. 2004; Keim and Madhavan 1995). Specifically, this study hypothesizes that informed traders will use larger trades on rising markets (i.e., high liquidity markets) than on falling markets (i.e., low liquidity markets). Our empirical results support this hypothesis.

The remainder of this article is arranged as follows: Section 3.2 presents the motivation and background of the present study and hypothesis development; section 3.3 contains details about the data, the sample selection used in this study, and the method; the empirical results are discussed in section 3.4; and section 3.5 offers some conclusions.

3.2 Motivation, Background, and Hypotheses

Theoretical models about the behavior of informed traders suggest that they spread trades over time in order to maximize profits from their private information (Eom and Hahn 2005; Kyle 1985)[60] or by trading when liquidity is high (i.e., during an opening period) (Admati and Pfleiderer 1988). However, these models do not explicitly address the choice of trade size used by an informed trader. For example, the models do not identify the optimal trade size used by these traders to hide trades in order to protect their information from being revealed too quickly. Despite a large number of studies that examine the role and behavior of profit-

[60]Specifically, Eom and Hahn (2005) find that frequency of trades has a larger effect on future option price volatility than trade size, which supports the hypothesis that traders exercise their informational advantage by using a series of small-sized trades over time instead of using one large trade.

maximizing informed traders, the questions about exactly how informed traders trade and their choice of trade size remain largely unanswered.

Barclay and Warner (1993) propose the stealth trading hypothesis to explain the behavior of informed traders. They suggest that informed traders use several medium-sized trades to avoid detection. The medium-sized trades should not be too small because a small-sized trade delays the acquisition of the desired (large) position, increases the likelihood that the private information will be revealed, and incurs a fixed cost per trade. On the other hand, if a large trade is not broken up, it can cause an unnecessarily large price impact[61] because it will probably attract the attention of intermediaries or public investors. Using a sample of NYSE stocks from 1981 to 1984, Barclay and Warner find empirical evidence supporting their stealth trading hypothesis.[62]

Anand et al. (2005) and Chakravarty (2001) examine stealth trading using a sample from the November 1990 to January 1991 NYSE TORQ dataset. Their results are consistent with Barclay and Warner's (1993) stealth trading hypothesis and show that medium-sized trades are associated with a disproportionately large cumulative price change relative to their proportion of all trades and volume. More important, they find that institutions rather than individuals are the source for the disproportionately large cumulative price change of medium-sized trades, which implies institutional investors are indeed informed.

Anand and Chakravarty (2006) examine stealth trading in options markets. They demonstrate that for the overall sample a significant amount of price

[61]See the theoretical model by Easley and O'Hara (1987), the empirical evidence about institutional equity trades by Chan and Lakonishok (1993, 1995) and Chiyachantana et al. (2004), and the empirical evidence on futures markets discovered by Berkman et al. (2005) and Frino and Oetomo (2005).

[62]In fact, they test the stealth trading hypothesis against alternative two hypotheses: the public information hypothesis and the trading volume hypothesis.

discovery occurs through small (40%) and medium (41%) trades. In addition, they find that the strategic fragmentation of trades by informed traders depends on the liquidity of options contracts. Specifically, for liquid (illiquid) contracts, informed traders tend to use medium-sized (small-sized) trades.[63]

Lee and Yi (2001) argue that different trading mechanisms can result in different trade size choices by informed traders. Specifically, they examine the relationship between trade size and the extent of informed trading on the options (i.e., Chicago Board Options Exchange) and stock markets (i.e., New York Stock Exchange).[64] Using a sample of firms cross-listed on CBOE and NYSE from January 1989 to December 1990, Lee and Yi find that large trades are more informed than small trades on NYSE, while small trades are better informed than large trades on CBOE. They suggest that different trading mechanisms on the stock and options markets could explain these findings. In particular, as a result of the competitive market maker system on CBOE, large trades are not anonymous, and this feature enables option market makers to screen large informed investors more effectively. Therefore, large informed traders invest on a stock market, where their large trades are more anonymous.

Boehmer's (2005) study shows that execution costs on NASDAQ are higher (lower) than on NYSE for small (large) trades. This finding is attributed to

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[63]Anand and Chakravarty (2006) use a different method to compute how much each trade size category contributes to the total price change from the method used by Barclay and Warner (1993) and Chakravarty (2001). Anand and Chakravarty employ the information share method developed by Hasbrouck (1995, 2003).

[64]Lee and Yi (2001) report that for all trades (not classified by trade size) the adverse selection component of spread is marginally higher on CBOE (i.e., competing dealer market) than on NYSE. This is consistent with the finding by Heidle and Huang (2002) that the probability of informed trading is higher on NASDAQ (i.e., competing dealer market) than on NYSE (i.e., auction market with specialist).

differences in how informed traders submit orders[65]: That is, on NASDAQ, large informed orders can easily be detected by dealers[66]; therefore, large informed traders tend to split their orders and submit the split orders simultaneously to several dealers, which makes small NASDAQ orders informed and expensive to execute. In contrast, large informed orders on NYSE are usually not split because split orders are executed sequentially (i.e., causing large price impact costs and taking too much time to warrant their short-lived information); therefore, large informed traders on NYSE tend to submit larger orders directly to a specialist, who, in turn, executes these orders against standing public limit orders[67] and will not get a price improvement. On the contrary, uninformed small orders are chosen to execute by specialists and therefore get a price improvement.

Huang and Stoll (1996) report that the adverse selection component decreases with trade size on NASDAQ, and it increases with trade size on NYSE. They ascribe this result to two main factors: First, they suggest that NASDAQ dealers know their institutional customers well, and they know that many large (and also medium) trades are non-information driven, which supports Barclay et al.'s (2003) argument that NASDAQ dealers are well positioned to spot large informed trades; and second, the fact that the adverse selection component is significant on NYSE, especially for medium and large trades, could reflect the role of limit orders on NYSE (i.e., public investors who place limit orders lose to informed traders more than specialists and floor traders do).[68]

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[65]The findings by Bessembinder (2003) also support Boehmer's (2005) argument. Bessembinder analyzes a matched post-decimalization sample of NYSE and NASDAQ stocks and shows that the NASDAQ-NYSE price impact (i.e., the adverse selection component of effective spread) differential declines from \$0.77 for executions inside the quote (i.e., small trades) to \$-3.24 for executions outside the quote (i.e., large trades).
[66]Barclay et al. (2003) and Huang and Stoll (1996) also support this argument.
[67]See, for example, Huang and Stoll (1996) and Werner (2003).
[68]Werner's (2003) NYSE empirical evidence confirms this belief.

Several studies focus on dealers and specialists' relative ability to identify informed traders and compare dealers on NASDAQ and specialists on NYSE. Garfinkel and Nimalendran (2003) compare the degree of anonymity (i.e., the extent to which a trader is recognized as informed) on NYSE and NASDAQ. They find a significant difference between the two markets' average responses to insider trading: That is, the change in effective spreads as a result of insider trading is larger on NYSE than on NASDAQ. This supports the idea that there is less anonymity on NYSE than on NASDAQ. Heidle and Huang (2002) analyze firms that transfer to an alternative exchange structure and show that traders are more anonymous on a competing dealer market (i.e., NASDAQ) than on an auction market (i.e., NYSE). Their results indicate that competing dealers on an anonymous, electronic-screen-based market such as NASDAQ have more difficulty discerning informed traders from liquidity traders.[69] In other words, NYSE, where the execution of the entire order flow goes through one specialist on the exchange floor, identifies informed traders and uninformed traders more easily. Using German stock market data, Grammig et al. (2001) empirically analyze whether the degree of trader anonymity is related to the degree of informed trading by comparing the probability of information-based trading on non-anonymous, traditional floor-based exchanges to an anonymous computerized trading system. Their results indicate that the probability of informed trading is significantly lower

[69]This finding by Garfinkel and Nimalendran (2003) and Heidle and Huang (2002) is inconsistent with the finding by Boehmer (2005), Huang and Stoll (1996), and Lee and Yi (2001) discussed earlier. There are two reasons for this discrepancy: First, the difference in relative ability between NASDAQ dealers and NYSE specialists discussed by Boehmer, Huang and Stoll, Lee and Yi is conditional on trade size, whereas the difference in relative ability between dealers and specialists identified by Garfinkel and Nimalendran and Heidle and Huang is for overall sample trades (i.e., unconditional on trade size); and second, the sample stocks covered by these studies are quite different (e.g., the sample stocks in the studies by Boehmer, Huang and Stoll, and Lee and Yi are broader than those used by Garfinkel and Nimalendran and Heidle and Huang.

on the floor of the Frankfurt Stock Exchange than on the anonymous computerized trading system, which supports the hypothesis that informed traders have a preference for anonymous markets.

So far, studies that examine stealth trading focus entirely on NYSE, and no studies have been conducted on other markets (e.g., a pure limit order market). NYSE employs a hybrid trading system, including specialists and public limit orders; however, previous studies (e.g., Boehmer 2005; Garfinkel and Nimalendran 2002; Grammig et al. 2001; Heidle and Huang 2002; Huang and Stoll 1996; Lee and Yi 2001) suggest that market structure could determine the choice of trade sizes by informed traders. The ability of market makers to detect informed trades plays an important role in determining the choice of trade sizes by informed traders. Different market architectures induce investors with private information to behave differently and adopt different trading strategies in order to hide their trades and maximize the value of their private information. Specifically, following previous studies on U.S. markets (e.g., Boehmer 2005; Garfinkel and Nimalendran 2002; Grammig et al. 2001; Heidle and Huang 2002; Huang and Stoll 1996; Lee and Yi 2001), the present study argues that informed traders will be less likely to break up their trades in a pure limit order market because this market has no market intermediaries, and theoretically, it is fully anonymous. As a result, in a pure limit order market, medium-to-large sized trades tend to be better informed. These arguments lead to hypothesis 1:

Hypothesis 1: In a pure limit order market, informed traders are concentrated in the medium-to-large-sized trade category.

In the present study, data from the Stock Exchange of Thailand (SET), a purely limit order market, is used to test hypothesis 1. In order to test hypothesis 1, this study examines the proportion of a stock's cumulative price change that occurs in each trade size group and compares the proportion of the price change for each trade size group to its proportion of all trades and volume.[70]

In addition, this study examines how stealth trading operates under different market conditions (i.e., bullish and bearish) in order to discover whether informed traders' trade size choices are influenced by market conditions. There is no a priori theory that states clearly how market conditions influence the way informed traders hide their trades to protect the value of their private information; however, the present study proposes that there are several reasons that might encourage informed investors to use larger-sized trades on a bullish market than on a bearish market. First, the liquidity volume is generally higher on a bullish market than on a bearish market. Some studies (e.g., Grinblatt et al. 1995)[71] suggest that momentum strategies are stronger on a bull market than on a bear market; therefore, on a bullish market, it is less necessary for informed traders to break up large trades because they can hide these large trades during high liquidity volume periods. Second, Campbell et al. (2004) argue that institutional traders employ different size trades according to volume and volatility. Specifically, they suggest that during highly volatile days (and, therefore, high volume days[72]) informed traders are particularly urgent about their trades and need to trade in large sizes. Third, as suggested by Keim and Madhavan (1995), the benefits of trading over a longer horizon are largest in thin markets, so trade duration should decrease with market liquidity after correcting for order size. Keim and Madhavan point out that during a

[70]See Barclay and Warner (1993) and Chakravarty (2001).
[71]Grinblatt et al. (1995) find that institutional investors typically buy past winners, but most of them do not systematically sell past losers.
[72]In general, a positive relationship exists between volume and volatility (Karpoff 1987).

down (up) market, when liquidity is low (high), an order break-up strategy is more (less) beneficial. These arguments lead to hypothesis 2:

Hypothesis 2: Informed traders are more concentrated in larger-sized trades on a bullish market than on a bearish market.

Hypothesis 2 is tested with a procedure similar to the one used to test hypothesis 1: That is, this study examines the proportion of a stock's cumulative price change that occurs in each trade size group under the two market conditions, and then under each market condition, the proportion of the price change for each trade size group is compared to its proportion of all trades and volume. Again, data from SET, a purely limit order market, are used to test hypothesis 2.

3.3 Data and Methodology

3.3.1 Data

We retrieve the transactions data for all securities traded on SET from January 2002 to October 2002. The data were captured on-line in real time from Reuters and contain a time sequence of quote and trade records. Each trade record contains security name, date, time, and traded price, while each quote record contains the prevailing best bid and ask. The sample data are divided into two distinct periods according to the market condition[73]. As shown in Table 3.1, the first period is from 24 January 2002 to 13 June 2002, when the SET index level increases from 327 to 426 (i.e., a market return of 30.3%), which signifies a bullish market. The second period is from 14 June 2002 to 14 October 2002, when the SET

[73] The following criteria are used to select the bull and bear periods. Based on the data available to us, we select two periods with the one period where the market goes up, and the other where the market goes down. In addition, to mitigate any biases, the absolute price change of the Thai market index in such two periods is required to be as close as possible, and such two periods should have roughly the same length. As a robustness check, we also redo all of the analyses on other data periods. The results, not reported, are primarily similar to those on the original data periods.

index declines from 426 to 323 (i.e., a market return of -24.2%), which indicates a bearish market. There are 93 trading days in the first period and 82 days in the second period.

There are some restrictions for stocks analyzed in the present study. An active trading day is defined as a day with a minimum of 20 trades, and to be included into the analyses, a stock must have at least 150 active trading days in each of the two subperiods. The first trade of the day is excluded from the analyses because it represents an overnight price change and occurs under batch-auction trading rather than under the continuous trading that occurs during normal trading hours.

In order to maximize the chance of detecting any stealth trading, this study only examines stocks that experience significant price changes during our sample period (Barclay and Warner 1993; Chakravarty 2001). Specifically, the stocks that display at least a 5% increase in price over the first period and a 5% decrease in price over the second period are selected[74]. As a result, 73 liquid stocks, with approximately 2.5 million trades, are included in the sample. Table 3.1 presents the overall characteristics of our sample. The equally weighted returns of these 73 stocks are higher than the corresponding market returns in both periods: 53.7% on the bull market, and -52.4% on the bear market. On the bull market, the minimum stock return is 10.2%, while the maximum stock return is 237.7%. On the bear market, the maximum stock return is -5.4%, and the minimum stock return is -255.2%. These large price changes make it likely that any stealth trading by informed traders will be detected. Both average market capitalization and volume-

[74] The analyses on the stocks with price change smaller than 5% are also performed. Basically, the results (not reported here) for those stocks are qualitatively similar to the reported results (for stocks with price change greater than 5%).

weighted traded price are higher in Period 2 than in Period 1. This could be, in part, because market capitalization is measured at the beginning of each period.

3.3.2 Methodology

3.3.2.1 Trade Size Classifications

The first trade for morning and afternoon sessions and the last trade of the day are identified and excluded from the analyses because these trades occur under batch auction trading. The remaining trades occur during continuous trading during normal trading hours (i.e., 10.00 AM to 12.30 PM and 14.30 PM to 16.30 PM) and are classified according to their sizes. Previous studies base trade size categories on the absolute number of shares traded. For example, Anand et al. (2005), Barclay and Warner (1993), and Chakravarty (2001) classify the trade sizes of 100 to 499 shares as small, 500 to 9,999 shares as medium, and more than 10,000 shares as large.[75] However, the present study does not follow this trade size classification procedure because our preliminary analysis of trade sizes on SET suggests that trade sizes on SET are significantly different from trade sizes on U.S. markets. The mean trade size of our sample stocks is 23,920 shares, while the mean trade size for NYSE stocks is approximately 2,500 shares.[76] In order to deal with the difference in trade sizes and make the results from our study comparable to existing studies,

[75]In fact, Barclay and Warner (1993) divide the small size category into four subcategories (i.e., 100, 200, 300, 400 shares) and the medium category into five subcategories (i.e., 500 shares, 600–900 shares, 1,000–1,900 shares, 2,000–4,900 shares, and 5,000–9,900 shares). Chakravarty (2001) divides the medium trade size category into four subcategories (i.e., 500–999 shares, 1,000–2,999 shares, 3,000–5,999 shares, and 6,000–9,999 shares.

[76]Lin, Sanger, and Booth (1995) report that the average trade size for their 150 NYSE common stocks during 1988 is 2,034, and the average trade size for all firms on NYSE in 1988 is 2,303. Chakravarty (2001) reports that the average trade size for 97 NYSE firms in the TORQ database from November 1990 to January 1991 is 2,535. Werner (2003) reports that the average trade size for 101 NYSE stocks from July 1997 to October 1997 is 1,926. In Barclay and Warner's (1993) study, the average trade size for 108 NYSE tender offer target firms from 1981 to 1984 is approximately 1,300 shares.

trade sizes are divided into percentile categories. As in the Chan and Lakonishok (1993, 1995) and Lin, Sanger, and Booth (1995) studies, the present study uses seven trade size categories. For each period and each firm, all trades are ordered by their size in shares. For each period, each firm's trades are divided into the following seven percentile categories: less than p25, p25 to p50, p50 to p75, p75 to p90, p90 to p95, p95 to p99, and larger than p99. The share size cutoffs corresponding to each percentile are based on each firm's trade size distribution in each period; therefore, the cutoffs vary in absolute share size across firms and periods. This trade size classification is used to define trade sizes for each firm relative to the order flow experience for the firm over each of the two periods.[77]

3.3.2.2 Percentage Cumulative Price Change by Trade Size Categories

As in the Barclay and Warner (1993) and Chakravarty (2001) studies, the present study defines the price change of each trade as the difference between the price of the current trade and the price of the previous trade (i.e., *Price Change*), and the change in price from the first to last trade during each sample period for

[77] A comparison of trade sizes based on number of shares is inappropriate because of the differences in prices between stocks themselves and between Thai stocks and U.S. stocks. For example, a 10,000-share trade may be a small-sized trade for some stocks (e.g., small-cap, low-priced stocks), but it could be a large-sized trade for certain stocks (e.g., large-cap, high-priced stocks). A 9,300-share trade is a median-sized trade for our sample stocks in Period 1; however, it is a large trade on the U.S. markets (i.e., it is larger than 90% in Barclay and Warner [1993] and Chakravarty [2001]). In addition, when the size of a trade is considered in terms of dollar absolute value, although the median or mean trade sizes in shares of Thai stocks are much larger than those of U.S. stocks, average trade size in dollar value of Thai stocks is much smaller than the average trade size in dollar value of U.S. stocks. The mean trade size of our sample stocks is 23,920 shares, and the volume-weighted average trade price for that period is around 10.33 baht. Therefore, the mean trade size in dollar value will be $\frac{23,920 \times 10.33}{40}$ (where approximately 40 baht is equal to 1 U.S. dollar), which is nearly US$6,200, while the corresponding number for U.S. stocks is roughly US$57,820 (see Chakravarty 2001; Lee and Radhakrishna 2000). Therefore, in order to make a comparison of trade sizes across two markets and across stocks with different price levels meaningful, the classification of trade sizes based on percentile ranking is adopted in our study.

each firm (i.e., *Total Price Change*) is computed. Then, for each firm, the trade-by-trade price changes for each trade size category are summed and divided by *Total Price Change* to obtain a percentage cumulative price change. Finally, the cumulative price change for each trade size is the weighted average of the cumulative price changes of that size category across 73 individual stocks, where the weight of each stock is its *Total Price Change*.

3.3.2.3 Percentage Cumulative Quote Revision by Trade Size Categories

The present study uses Cooney and Sias' (2004) procedure and computes quote change in addition to price change. Price changes caused by a trade are sometimes influenced a trader's impatience and not by an information advantage, which results in bid-ask bounce; therefore, the present study proposes that a better measure for the information content of a trade is the market's respond to each trade. As a result, the quote revision impact (i.e., *Quote Change*) is computed as the quote midpoint prevailing at the time of the subsequent trade less the quote midpoint in effect at the time of the current trade. The cumulative quote revision (i.e., *Total Quote Change*) is the sum of the quote revision impact associated with each trade from the first to last trade in each of the sample periods. For each firm, the trade-by-trade quote changes for each trade size category are summed and divided by *Total Quote Change* to obtain a percentage cumulative quote revision for each trade size category. Finally, the cumulative quote revision for each trade size is the weighted average of the cumulative quote revisions of that trade size category across 73 individual stocks, where the weight of each stock is its *Total Quote Change*.

3.3.2.4 Percentage of Trades and Percentage of Volume of Trades

As in the Barclay and Warner (1993), and Chakravarty (2001) studies, the percentage of trades for all sample stocks during each sample period is computed as the sum of all trades in each category divided by the sum of all trades in all categories. In addition, the percentage of volume of trades for all sample stocks during each sample period is computed as the sum of all volume of trades in each category divided by the sum of all volume of trades in all categories. The percentage of trades and percentage of volume of trades are used to test the stealth trading hypothesis against the public information hypothesis and the trading volume hypothesis,[78] respectively.

3.4 Empirical Results

3.4.1 Descriptive Statistics of Trade Sizes

Table 3.2 presents the characteristics of trades for the 73 stocks divided by trade size. For each period, trades are classified by seven trade size categories. As expected, for both periods, trade size as measured by average and median number of shares per trade and baht volume per trade increases with the trade size percentile. For example, in Period 1, the average number of shares per trade (baht volume per trade) is 1,578 shares (15,448 baht) for the less than p25 category and increases to 34,424 shares (356,796 baht) for the p75 to p90 category and 425,307

[78]The public information hypothesis and the trading volume hypothesis are two alternative hypotheses to the stealth trading hypothesis. The public information hypothesis predicts that the percentage cumulative stock price change occurring in a given trade size category is directly proportional to the percentage of transactions in that trade size category. The trading volume hypothesis predicts that the percentage cumulative stock price change in a given trade size category is proportional to the percentage of the total trading volume in that category. Of course, the trading volume hypothesis assumes that an additional 10,000-share purchase would have the same cumulative impact on the stock price regardless of whether the purchase is transacted in, for example, two 5,000-share trades or in five 2,000-share trades.

shares (4,382,062 baht) for the largest size category. The figures are similar for Period 2.

The trading activity is much livelier on the bull market than on the bear market, as shown by the larger daily number of trades, larger daily baht volume of trades, and larger daily number of shares traded on the bull market. Specifically, it appears that trading activity in Period 1 is approximately two times as dynamic as the trading activity in Period 2. In addition, for any trade size category, trade size in shares (as measured by average number of shares per trade or median number of shares per trade) increases as the market condition becomes more bullish. Table 3.2 shows that trade sizes are larger on the bullish market than on the bearish market, which suggests that informed traders prefer larger-sized trades in a high volume period because it is easier to camouflage their trades among a large number of liquidity traders.

3.4.2 Choice of Trade Sizes by Informed Traders Under a Pure Order-driven Market

In order to determine informed traders' trade size choices, the present study examines how much a stock's cumulative price/quote change over the sample periods is attributable to trades in each of the seven trade size categories. Table 3.3 presents descriptive data about the average percentage cumulative stock price change, the average percentage cumulative stock quote change in each of the seven trade size categories, the corresponding percentage of trades, and the corresponding volume percentages. The results presented in Table 3.3 indicate that small trades (i.e., trades below the median trade size) account for an estimated -82.3%[79] (-45.1%) of the cumulative price (quote) change and comprise 43.8% of the transactions and 5.4% of the volume. The trades in the p50 to p75 category produce 13.9% (1.8%) of the cumulative price (quote) change and account for 27.9% of the transactions and 13.9% of the volume. On the other hand, the four top trade size categories (i.e., p75–p90, p90–p95, p95–p99, and larger than p99) account for 168.4% (143.1%) of the cumulative stock price (quote) change and comprise 28.3% of the transactions and 80.8% of the volume. As a result, the four top trade size categories, both as a group and as individuals, appear to play a disproportionately large role in the cumulative price change and quote change relative to their proportion of trades and volume in the sample.

There appears to be no support for the public information hypothesis. Trades in the less than p25 category and p25 to p50 category produce approximately -49.7% and -32.6% of the cumulative stock price change, respectively, but they account for 19.7% and 24.1% of all trades. Trades in the p50 to p75 category produce approximately 13.9% of the cumulative stock price change, but they account for 27.9% of all transactions. Trades in the four top categories produce 168.4% of the cumulative price change, while they account for only 28.3% of all trades.

In addition, there appears to be limited support for the trading volume hypothesis because the percentage cumulative price change for any trade size category is more or less proportional to the fraction of the total trading volume in that category. Despite the limited support for the trading volume hypothesis, the

[79]The negative price change suggests that small-trade investors, on average, are picked off because they trade in the opposite direction to the market movement (i.e., sell in rising markets and/or buy in falling markets).

percentage cumulative price change for each of the four top size categories is still much higher than its fraction of the total trading volume. This supports the hypothesis that the four top trade size categories are predominantly used by informed traders. The regression analyses in the next section formally tests the stealth trading hypothesis against the two alternative hypotheses (i.e., the public information hypothesis and the trading volume hypothesis).

The results in Table 3.3 support hypothesis 1 and suggest that on SET (i.e., a pure limit order market) informed traders hide trades by using larger-sized trades more often than informed traders on U.S. market with market makers who are able to screen out informed trades. The results from the present study are compared to the U.S. market using the percentage cumulative price change, the percentage of trades, and the percentage of trading volume for each trade size category reported by Barclay and Warner (1993) and Chakravarty (2001) (see Table 3.4). Panel A and panel B, Table 3.4 show that informed traders prefer medium-sized trades: That is, the percentage cumulative price change for a medium-sized trade reported by Barclay and Warner (Chakravarty) are 92.8% (77.2%), while this category represents only 45.7% (53.8%) of the total transactions and only 63.5% (45.5%) of the total trading volume. In addition, only the first three medium-size trade subcategories are used by informed traders to hide their trades.

As shown in panel A, trades in the 5,000 to 9,900 shares category produce only 7.4% of the cumulative price change, but they account for 13.5% of all trading volume; therefore, the percentage (i.e., 7.4%) of the price change is smaller than predicted by the trading volume hypothesis. Similarly, in panel B, trades in the 6,000 to 9,999 shares category produce 6.2% of the cumulative price change and account for 7.7% of all trading volume. Again, the percentage (6.2%) of the price change is smaller than predicted by the trading volume hypothesis. Panel A (B) indicates informed traders use trades with sizes between p50 and p95 (p40 to p90).[80] This finding highlights the importance of hypothesis 1, which predicts that informed traders in a pure limit order market concentrate in the medium-to-large size trade category.

Table 3.3 shows that trades in the p75 and above categories produce larger cumulative price changes than predicted by their fractions of the total number of trades and the total trading volume in their corresponding category. In the p75 and above categories (i.e., p75–p90, p90–p95, p95–p99, and larger than p99), the percentage of the stock price change is approximately 168.4%, which is much larger than the corresponding fraction of the total number of trades (i.e., 28.3%) and the corresponding percentage of the total trading volume (80.8%).

For small trades, the percentage cumulative price changes are negative in both Thai market (i.e., less than p25 and p25-p50 in Table 3.3) and the U.S. markets (i.e., 100-499 shares in Table 3.4). However, the negative percentage cumulative price changes for the small trades on Thai markets are much greater in magnitude than those on the U.S. markets. There are two possible (not mutually exclusive) explanations for the observation. First, the negative (positive) values of price or quote changes for a particular trade size category suggest that investors using such trade size category are net exploited (informed). Therefore, the much larger negative price and quote changes associated with small trades on the Stock Exchange of Thailand (SET) simply imply that they are more often picked off by

[80]Trades between 50% and 95% (see panel A) refer to a combination of the following three trade size subcategories: 500 to 900 shares, 1,000 to 1,900 shares, and 2,000 to 4,900 shares. Trades between 40% and 90% (see panel B) refer to a combination of the following three trade size subcategories: 500 to 999 shares, 1,000 to 2,999 shares, and 3,000 to 5,999 shares.

large trades than are small trades on the U.S. markets. In other words, the extent to which small trades are relatively less informed or more liquidity-driven or exploited than large trades is larger in SET than in the U.S. markets. Second, the small trades (i.e., less than p50) on the U.S. markets are usually transacted within the existing quoted spread. By contrast, small trades on SET are always transacted at the quoted bid (for sell trades) or quoted ask price (for buy trades). This (partially) explains why small trades on SET are associated with large negative price changes, as compared with small trades on the U.S. markets.

The results of the present study empirically support hypothesis 1. This study, therefore, contributes to the existing literature by showing the effect of trading structures (pure limit order market or fully anonymous market structure versus markets with intermediaries) on informed traders' trade size choices.

3.4.3 Informed Traders' Trade Size Choices Under Different Market Conditions

Table 3.5 shows the percentage cumulative price change, percentage cumulative quote change, percent of transactions, and percent of trading volume for each of the seven trade size categories, classified by market conditions (i.e., rising market in panel A and falling market in panel B). Markets conditions do not appear to have a clear impact on informed traders' trade size choices. Panel A, Table 3.5 shows that the smallest trades (i.e., the less than p25 category) account for an estimated 34.6% (17.2%) of the cumulative price (quote) change and comprise 19.5% of the transactions and 1.2% of the volume. The trades in the p25 to p50 and p50 to p75 categories produce a negative percentage cumulative price change. On the other hand, the four top trade size categories (i.e., p75–p90, p90–p95, p95–p99, and larger than p99) account for 127.9% (134.2%) of the cumulative stock price (quote) change and comprise 28.6% of the transactions and 81.2% of the volume. Therefore, on the rising market, the four top trade size categories appear to play a disproportionately large role in the cumulative price change and quote change relative to their proportion of trades and volume in the sample. Similarly, the results shown in panel B are consistent with the results shown in panel A. On the falling market, the four top size categories account for 194.6% (148.3%) of the cumulative stock price (quote) change and consist of 27.7% of the trades and 79.7% of the trading volume and have a disproportionately larger proportion of the overall price (quote) change relative to their proportion of transactions or trading volume in the falling period.

The average trade sizes of the four top categories on the rising market are much larger than average trade sizes on the falling period. Rising (falling) markets are generally associated with high (low) volume periods, and order break-up strategies under bullish (bearish) market conditions become less (more) beneficial, which leads informed traders to use larger sized trades on bull markets than on bear markets. Although it appears that informed traders always prefer large size trades (i.e., p75 and larger) on bull and bear markets, on the bull market, the average trade sizes for the four top categories are 34,424 shares, 70,383 shares, 144,245 shares, and 425,307 shares, respectively, whereas on the bear market, the corresponding average trade sizes are 26,356 shares, 53,219 shares, 109,686 shares, and 335,329 shares, respectively. These findings are consistent with hypothesis 2 (i.e., informed traders are more concentrated in larger-sized trades on a bullish market than on a bearish market).

3.4.4 Choice of Trade Sizes by Informed Traders: Multivariate Analysis

A formal multivariate test is conducted to separate stealth trading from public information and trading volume, supplementing the univariate results shown in Table 3.3 and 3.5. Table 3.6 shows the coefficients and adjusted R-square of the regression[81] of the percentage cumulative price change (panel A) and the percentage of cumulative quote change (panel B) on dummy variables for each of the seven trade size categories and the percentage of transactions (regression [1]) and percentage of volume (regression [2]). The regression is pooled across all 73 sample stocks. The regressions in each panel are run for the combined sample periods and separately for each of the two sample periods. The results of the equality tests of trade size dummy variables are also reported.

According to the public information hypothesis, the coefficient on each trade size dummy variable should be 0, and the coefficient on the percentage of trades should be 1. The results of regression (1) (see panel A, Table 3.6) are not consistent with the public information hypothesis in all periods. The results demonstrate that the percentage price changes are smaller than predicted by the public information hypothesis for less-than-median-sized trades (i.e., the first two smallest categories) and larger than predicted in the larger-than-median-sized trades (i.e., the last five categories). In particular, for the top four categories, the percentage price changes are much larger than the percentage of transactions: That is, the coefficients of the top four categories are larger than 1, while the coefficient of the P50-P75 dummy variable is 0.511. In addition, the results from the equality

[81] As in Barclay and Warner's (1993) study, in order to reduce heteroskedasticity in the dependent variables (i.e., the percentage cumulative price change and the percentage cumulative quote change), the regression in the present study is weighted least square, where weight is the absolute cumulative price (or quote) change for that stock over the sample period.

tests of trade size dummy variables show that the hypothesis that predicts the coefficient in the P50-P75 category is equal to the coefficient in the P75-P90 category can be rejected at the 0.054 level of significance; however, the hypotheses that predict the coefficients of the last four category dummies (i.e., P75-P90, P90-P95, P95-P99, and larger than P99) are equal cannot be rejected at any conventional level of significance. These results imply that the last four groups are the trade sizes most preferred by informed traders, which is consistent with the univariate results in Table 3.3 and confirms our hypothesis.

In Table 3.6, the results in regression (2) for the trading volume hypothesis also echo the results in regression (1) for the public information hypothesis. The results for regression (2) (see panel A, Table 3.6) are not consistent with the trading volume hypothesis in all periods. The results demonstrate that the percentage price changes are smaller than predicted by the trading volume hypothesis for the P0-P25 category, as represented by the statistically significant coefficient of -0.504, and larger than predicted in the last four categories, as shown by the statistically significant coefficient of 0.854, 0.805, 0.912, and 0.710, respectively. Generally, these results indicate that informed traders are concentrated in the top quartile trade size (P75 and larger), which is consistent with the univariate results in Table 3.3 and confirm our hypothesis.

Hypothesis 1 is supported more in the down period than in the up period. The results for the down period resemble the results in all periods in terms of magnitude and significance of the dummy variable coefficients (see panel A, Table 3.6). The coefficients for the up period, however, are nearly all statistically insignificant.

The results shown in panel B are based on the percentage cumulative quote change as the regression dependent variable, and they are qualitatively similar to those shown in panel A, where the percentage cumulative price change is the regression dependent variable. The results in panel B agree with the univariate results shown in Table 3.3, and they also confirm the robustness of using different measures of the impacts of trades on stock prices and quotes.

3.5 Conclusion

This study examines stealth trading for 73 liquid stocks listed on SET, a pure limit order market. As a result of market makers' ability to detect informed trades, it is difficult to apply the result of studies that examine stealth trading on U.S. markets, which have market makers, to a pure limit order market such as SET, which has no market makers. The present study hypothesizes that unlike stealth trading on specialist (e.g., NYSE) or dealer (e.g., NASDAQ) markets, where medium-sized trades are most informed, in a pure limit order market, where there are no market makers who can screen out informed trades, informed trades tend to use relatively larger-sized trades. Using intraday trade and quote data for the 73 most-liquid stocks over two periods with different market conditions, the present study finds that the medium-to-large size trade groups (i.e., percentile75–percentile90, percentile90–percentile95, percentile95–percentile99, and larger than percentile99) account for 168.4% (143.1%) of the cumulative stock price (quote) change and comprise 28.3% of the transactions and 80.8% of the volume. This finding indicates that these trade groups play a disproportionately large role in the cumulative price change and quote change relative to their proportion of trades and volume in the sample. The existing results for U.S. markets show that informed traders employ trade sizes that are between percentile 50 and percentile 95 (Barclay and Warner 1993) and percentile 40 and percentile 90 (Chakravarty 2001); therefore, these results support our hypothesis that on SET (i.e., a pure limit order market) informed traders are able to trades by using larger-sized trades than the trades used by informed traders on U.S. market (i.e., markets with market makers who are able to screen out informed trades).

The present study also analyzes trading for 73 liquid stocks to discover whether informed traders' trade size choices vary with market conditions. The results indicate that on rising and falling markets the four top trade size categories (i.e., percentile 75 and larger) play a disproportionately large role in the cumulative price change and quote change relative to their proportion of trades and volume in the sample. However, the average trade sizes for these four top categories on the rising market are much larger than the average trade sizes on the falling market. Therefore, the results show that informed traders use large-sized trades more frequently on a bullish market than on a bearish market, and they support the hypothesis that high trading volume on the bullish market helps informed traders camouflage their trades.

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Table 3.1
Overall Sample Characteristics

This Table contains the trading characteristics for 73 liquid stocks listed on SET from January 2002 to October 2002. The sample period is divided into two subperiods: a bull market and a bear market. The first period (i.e., January 2002 to June 2002) is a bull market, while the second period (i.e., June 2002 to October 2002) is a bear market.

	Period 1	**Period 2**
	(Jan 24, 2002 - Jun 13, 2002)	**(Jun 14, 2002 - Oct 14, 2002)**
Number of stocks	73	73
Number of trading days (days)	93	82
Average market cap (million baht)	12,901	13,024
Volume-weighted trade price (baht)	10.33	11.75
Market return	30.3%	-24.2%
Equally-weighted 73-stock return	53.7%	-52.4%
Minimum stock return	10.2%	-255.2%
Maximum stock return	237.7%	-5.4%

Table 3.2
Summary of Trading Characteristics by Trade Size

This Table contains the trading characteristics for 73 liquid stocks listed on SET from January 2002 to October 2002. The sample period is divided into two subperiods: a bull market and a bear market. The first period (i.e., January 2002 to June 2002) is a bull market, while the second period (i.e., June 2002 to October 2002) is a bear market. The sample characteristics are divided based on trade size. The trade size categories are constructed in the following way: For each period and each firm, all trades are ordered by their size in shares. For each period, each firm's trades are divided into the following seven percentile categories: less than p25, p25 to p50, p50 to p75, p75 to p90, p90 to p95, p95 to p99, and larger than p99.

	Period 1 (Jan 24, 2002 - Jun 13, 2002)							Period 2 (Jun 14, 2002 - Oct 14, 2002)						
	<25	**25-50**	**50-75**	**75-90**	**90-95**	**95-99**	**>99**	**<25**	**25-50**	**50-75**	**75-90**	**90-95**	**95-99**	**>99**
Average number of shares per trade	1,578	4,522	12,816	34,424	70,383	144,245	425,307	1,251	3,461	10,379	26,356	53,219	109,686	335,329
Median number of shares per trade	1,000	4,000	10,000	27,500	50,000	100,000	300,000	1,000	3,000	10,000	20,000	50,000	100,000	268,500
Median trade size corresponding to the percentile cutoffs	<2,000	2,000-9,300	9,300-20,000	20,000-50,000	50,000-100,000	100,000-300,000	>300,000	<2,000	2,000-5,000	5,000-19,100	19,100-50,000	50,000-88,700	88,700-202,500	>202,500
Baht volume per trade (baht)	15,448	51,857	124,778	356,796	755,922	1,477,807	4,382,062	13,374	44,991	112,159	315,230	659,472	1,292,331	3,853,029
Number of trades	313,961	394,366	440,383	276,866	88,867	76,506	17,556	188,096	220,321	270,349	153,587	52,522	42,951	9,957
Daily number of trades	3,376	4,240	4,735	2,977	956	823	189	2,294	2,687	3,297	1,873	641	524	121
Baht volume of trades (million baht)	4,850	20,451	54,950	98,785	67,177	113,061	76,931	2,516	9,912	30,322	48,415	34,637	55,507	38,365
Daily baht volume of trades (million baht)	52	220	591	1,062	722	1,216	827	31	121	370	590	422	677	468
Number of shares traded (million shares)	496	1,783	5,644	9,531	6,255	11,036	7,467	235	763	2,806	4,048	2,795	4,711	3,339
Daily number of shares traded (million share	5	19	61	102	67	119	80	3	9	34	49	34	57	41

Table 3.3
Percentage Cumulative Price Change, Percentage Cumulative Quote Change, Trades, and Volume by Trade Sizes

This Table contains the mean percentage of the cumulative stock price change and the cumulative stock quote change, percentage of trades, and percentage of share volume by trade sizes. The sample consists of 73 liquid Thai stocks with at least a 5% price change from January 2002 to October 2002. Trade sizes are divided into seven categories in the following way: For each firm, all trades are ordered by their size in shares, and each firm's trades are divided into seven percentile categories (i.e., less than p25, p25–p50, p50–p75, p75–p90, p90–p95, p95–p99, and larger than p99).

The stock price change for a given trade is defined as the difference between that trade's price and the previous trade's price. The stock quote change for a current trade is defined as the quote midpoint prevailing at the time of the subsequent trade less the quote midpoint in effect at the time of the current trade. For each stock, the percentage of cumulative price (quote) change for a trade of a given trade size is the sum of all stock price (quote) changes occurring in that trade size category divided by the total cumulative price (quote) change of that stock over the sample period. The weighted cross-sectional mean of the cumulative price (quote) change is computed and reported below, where the weights are the absolute value of the cumulative price (quote) change of each stock in the sample. The proportion of trade (volume) is the sum of all trades (volume) in a given trade size category divided by the total number of trades (volume) during the sample period.

Trade Size Category (Percentile)	Percentage cumulative price change	Percentage cumulative quote revision	Number of Trades	% of Trades	Volume	% of Volume
< 25	-49.7%	-0.2%	502,057	19.7%	730,805,800	1.2%
25 - 50	-32.6%	-44.9%	614,687	24.1%	2,545,949,100	4.2%
50 - 75	13.9%	1.8%	710,732	27.9%	8,450,148,100	13.9%
75 - 90	48.1%	34.0%	430,453	16.9%	13,578,852,200	22.3%
90 - 95	38.6%	40.0%	141,389	5.6%	9,049,873,800	14.9%
95 - 99	53.2%	48.5%	119,457	4.7%	15,746,757,600	25.9%
> 99	28.5%	20.6%	27,513	1.1%	10,805,562,300	17.7%

Table 3.4
Percentage Cumulative Price Change, Trades, and Volume by Trade Sizes from the U.S. Market

This Table contains the mean percentage of the cumulative stock price change, the percentage of trades, and percentage of share volume by trade sizes for the U.S. stock sample from Barclay and Warner (1993) (panel A) and Chakravarty (2001) (panel B).

Panel A: Barclay and Warner (1993)

Trade Size Category		Percentage cumulative price change	% of Trades	% of Volume
Small	**100-499 shares**	-2.3%	52.6%	12.1%
Medium	**500-900 shares**	24.1%	19.6%	12.9%
	1,000-1,900 shares	38.3%	15.2%	17.9%
	2,000-4,900 shares	23.1%	8.1%	19.2%
	5,000-9,900. shares	7.4%	2.9%	13.5%
Large	**10,000 shares up**	9.5%	1.7%	24.4%

Panel B: Chakravarty (2001)

Trade Size Category		Percentage cumulative price change	% of Trades	% of Volume
Small	**100-499 shares**	-1.2%	39.8%	3.0%
Medium	**500-999 shares**	30.9%	25.3%	7.6%
	1,000-2,999 shares	16.4%	16.6%	13.3%
	3,000-5,999 shares	23.6%	9.3%	17.0%
	6,000-9,999 shares	6.2%	2.5%	7.7%
Large	**10,000 shares up**	24.0%	6.4%	51.4%

Table 3.5
Percentage Cumulative Price Change, Percentage Cumulative Quote Change, Trades, and Volume by Trade Sizes and Market Conditions

This Table contains the mean percentage of the cumulative stock price change and the cumulative stock quote change, percentage of trades, and percentage of share volume by trade sizes and market conditions. The sample consists of 73 liquid Thai stocks with at least a 5% price change from January 2002 to October 2002. The sample period is divided into two subperiods; a bull market and a bear market. The first period (i.e., January 2002 to June 2002) is a bull market and is shown in panel A, while the second period (i.e., June 2002 to October 2002) is a bear market and is shown in panel B. Trade sizes are classified into seven categories in the following way: For each firm, all trades are ordered by their size in shares, and each firm's trades are divided into seven percentile categories (i.e., less than p25, p25–p50, p50–p75, p75–p90, p90–p95, p95–p99, and larger than p99).

The stock price change for a given trade is defined as the difference between that trade's price and the previous trade's price. The stock quote change for a current trade is defined as the quote midpoint prevailing at the time of the subsequent trade less the quote midpoint in effect at the time of the current trade. For each stock, the percentage of cumulative price (quote) change for a trade of a given trade size is the sum of all stock price (quote) changes occurring in that trade size category divided by the total cumulative price (quote) change of that stock over the sample period. The weighted cross-sectional mean of the cumulative price (quote) change is computed and reported below, where the weights are the absolute value of the cumulative price (quote) change of each stock in the sample. The proportion of trade (volume) is the sum of all trades (volume) in a given trade size category, divided by the total number of trades (volume) during the sample period.

Panel A: Up Market

Trade Size Category (Percentile)	Percentage cumulative price change	Percentage cumulative quote revision	Number of Trades	% of Trades	Volume	% of Volume	Average Trade Size (shares)
< 25	34.6%	17.2%	313,961	19.5%	495,568,700	1.2%	1,578
25 - 50	-55.7%	-63.6%	394,366	24.5%	1,783,376,900	4.2%	4,522
50 - 75	-6.9%	12.3%	440,383	27.4%	5,644,088,300	13.4%	12,816
75 - 90	22.2%	35.5%	276,866	17.2%	9,530,865,700	22.6%	34,424
90 - 95	26.1%	37.5%	88,867	5.5%	6,254,684,600	14.8%	70,383
95 - 99	51.3%	35.7%	76,506	4.8%	11,035,641,100	26.1%	144,245
> 99	28.3%	25.5%	17,556	1.1%	7,466,694,700	17.7%	425,307

Panel B: Down Market

Trade Size Category (Percentile)	Percentage cumulative price change	Percentage cumulative quote revision	Number of Trades	% of Trades	Volume	% of Volume	Average Trade Size (shares)
< 25	-104.4%	-10.0%	188,096	20.1%	235,237,100	1.3%	1,251
25 - 50	-17.6%	-34.2%	220,321	23.5%	762,572,200	4.1%	3,461
50 - 75	27.4%	-4.1%	270,349	28.8%	2,806,059,800	15.0%	10,379
75 - 90	64.8%	33.2%	153,587	16.4%	4,047,986,500	21.7%	26,356
90 - 95	46.8%	41.5%	52,522	5.6%	2,795,189,200	14.9%	53,219
95 - 99	54.4%	55.8%	42,951	4.6%	4,711,116,500	25.2%	109,686
> 99	28.6%	17.8%	9,957	1.1%	3,338,867,600	17.9%	335,329

Table 3.6
Regression Analysis of the Percentage Cumulative Price Change, Percentage Cumulative Quote Change, Percentage of Trades, and Percentage of Volume by Trade Sizes and Market Conditions

This Table presents the coefficients and adjusted R-square values of the weighted least square regressions, with the dependent variable as the percentage of cumulative stock price change (panel A) and the percentage of cumulative stock quote change (panel B). The independent variables include seven dummy variables that correspond to seven trade size categories and either percentage of transactions (i.e., *Ptrades*) in (1) or percentage of trading volume (i.e., *Pvolume*) in (2). The weights are the absolute percentage cumulative price/quote changes over the corresponding sample periods. *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively. This Table also shows the results of the equality test of the seven trade size dummy variables. The figures in the equality test table represent the *p*-values of the equality tests. The regression equations are as follows;

$$Y_{i,s} = \beta_0(P0-P25) + \beta_1(P25-P50) + \beta_2(P50-P75) + \beta_3(P75-P90) + \beta_4(P90-P95) + \beta_5(P95-P99) + \beta_6(>P99) + \beta_7 * Ptrades_{i,s} + \varepsilon$$

(1)

$$Y_{i,s} = \beta_0(P0-P25) + \beta_1(P25-P50) + \beta_2(P50-P75) + \beta_3(P75-P90) + \beta_4(P90-P95) + \beta_5(P95-P99) + \beta_6(>P99) + \beta_7 * Pvolume_{i,s} + \varepsilon$$

(2)

where $Y_{i,s}$ is the cumulative price (quote) change of the trade size category *i* (P0–P25, P25–P50, P50–P75, P75–P90, P90–P95, P95–P99, or >P99) for stock *s* in panel A (B). *P0–P25, P25–P50, P50–P75, P75–P90, P90–P95, P95–P99,* or *>P99* are dummy variables for the P0–P25, P25–P50, P50–P75, P75–P90, P90–P95, P95–P99, or >P99 trade size categories, respectively. In equation (1), $Ptrades_{i,s}$ is the percentage of transactions associated with trade size category *i* in stock *s*. In equation (2), $Pvolume_{i,s}$ is the percentage of trading volume associated with trade size category *i* in stock *s*.

Panel A: Percentage Cumulative Price Change

Independent Variables	All periods		Up period		Down period	
	(1)	(2)	(1)	(2)	(1)	(2)
P0 - P25	-0.931***	-0.504***	-0.917	0.331	-0.927***	-1.049***
P25 - P50	-0.001	0.146	-1.283**	-0.943*	0.922***	0.849***
P50 - P75	0.511**	0.564	-0.625	-0.521	1.360***	1.262***
P75 - P90	1.014***	0.854*	-0.059	-0.334	1.679***	1.605***
P90 - P95	1.186***	0.805**	0.834	-0.198	1.432***	1.450***
P95 - P99	1.362***	0.912*	1.137	-0.018	1.497***	1.501***
>P99	1.191***	0.710**	1.132	-0.172	1.220***	1.275***
Percent of trades	2.252		6.285*		-0.620	
Percent of volume		0.540		0.865		0.400
Adj R^2	0.03	0.03	0.00	0.00	0.39	0.39

Equality tests of trade size dummy variables

Tests	All periods		Up period		Down period	
	(1)	(2)	(1)	(2)	(1)	(2)
P0-P25 = P25-P50	0.025	0.084	0.702	0.117	0.000	0.000
P25-P50 = P50-P75	0.031	0.144	0.204	0.472	0.000	0.004
P50-P75 = P75-P90	0.054	0.330	0.288	0.784	0.014	0.012
P75-P90 = P90-P95	0.569	0.861	0.209	0.838	0.070	0.226
P90-P95 = P95-P99	0.455	0.693	0.552	0.764	0.563	0.690
P95-P99 = >P99	0.478	0.478	0.994	0.801	0.015	0.101

Panel B: Percentage Cumulative Quote Change

Independent Variables	All periods		Up period		Down period	
	(1)	(2)	(1)	(2)	(1)	(2)
P0 - P25	-0.000	0.001	-0.285	0.167	0.158*	-0.094*
P25 - P50	-0.446**	-0.439***	-0.936**	-0.818**	-0.104	-0.221***
P50 - P75	0.020	0.040	-0.135	-0.076	0.165**	0.117
P75 - P90	0.341**	0.376	0.195	0.127	0.406***	0.521***
P90 - P95	0.400*	0.423*	0.537	0.174	0.340***	0.577***
P95 - P99	0.485**	0.517*	0.537	0.138	0.458***	0.744***
>P99	0.206	0.226	0.516	0.056	0.034	0.332***
Percent of trades	-0.007		2.284		-1.414***	
Percent of volume		-0.149		0.222		-0.411
Adj R^2	0.04	0.04	0.01	0.01	0.35	0.34

Equality tests of trade size dummy variables

Tests	All periods		Up period		Down period	
	(1)	(2)	(1)	(2)	(1)	(2)
P0-P25 = P25-P50	0.099	0.077	0.333	0.081	0.020	0.244
P25-P50 = P50-P75	0.003	0.013	0.025	0.076	0.000	0.000
P50-P75 = P75-P90	0.066	0.088	0.373	0.678	0.003	0.000
P75-P90 = P90-P95	0.766	0.804	0.500	0.922	0.428	0.479
P90-P95 = P95-P99	0.589	0.594	1.000	0.931	0.082	0.030
P95-P99 = >P99	0.080	0.122	0.954	0.850	0.000	0.000