Essays on the Empirical Characteristics of Market Dynamics and Order Submission Aggressiveness in the Stock Exchange of Thailand (SET)

Ruangrong Suwankarn

PhD

University of York

Economics and Related Studies

March 2024

Abstract

This thesis contributes to the existing literature by undertaking three empirical studies addressing crucial issues within the market microstructure domain of the Stock Exchange of Thailand (SET). Following the introduction, Chapter 1 investigates how differences in market returns affect the price impact of trades in the SET, and how turnover and market capitalisation influence this relationship. Vector autoregression (VAR), impulse response function (IRF), cumulative impulse response function (CIRF), and panel regression are employed. The results show that entities listed in the SET100 index have low information asymmetry, low transaction costs, and high liquidity. The results also show that an escalation in turnover correlates with a heightened impact of trades on prices.

Chapter 2 examines the order submission aggressiveness of different types of trader in the Thai stock market - retail, foreign, and institutional - and the ways in which market conditions influence these order submission aggressiveness. Ordered logit regression methodology is employed, and the findings indicate distinct order submission aggressiveness among different trader types. Foreign traders are the most strategic traders implementing order submission aggressiveness, reflected by their intense activity in cancelling pending orders. Expressing a high willingness to cancel their existing orders underscores their sensitivity to the risk of non-execution, prompting them swiftly to adjust their pending orders with cancellations, and transition to more aggressive resubmissions.

Chapter 3 investigates the learning effects in traders arising from three separate market-wide applications of circuit breakers (MWCBs) during the first COVID-19 lockdown of March 2020. By using panel regression and difference-in-differences estimations, the results show consistent evidence across a wide range of different indicators that even though the first two MWCBs failed to restore market quality, their application nevertheless conditioned a dissimilar response to the third MWCB, allowing the stock exchange to curb volatility. This learning effect speaks directly to the individual effectiveness of MWCBs when used sequentially.

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Acknowledgements

First and foremost, my deep and sincere appreciation goes to my supervisors, Dr Maryam Alhalboni and Prof. Peter Spencer. I am full of appreciation for their time, guidance, support, patience, and suggestions over these years. I also thank them for giving their time so generously to discussing my work and providing detailed and insightful comments, which were essential in improving the thesis. Their continuous feedback has encouraged me to exceed my own limitations. It would have been impossible to complete this thesis without their exceptional supervision.

I also owe thanks to Prof. Peter Smith, who was my thesis advisory panel member and offered insightful advice and support. Sincere thanks also go to Dr Michael Shallcross and Miss Maigen Savory for helping me in various ways during my PhD study.

I gratefully acknowledge the Stock Exchange of Thailand (SET) for supplying the data used in this thesis, and in particular, Dr. Soraphol Tulayasathien, Senior Executive Vice President, Head of Corporate Strategy Division and Head of Sustainable Market Development Division of the SET, who provided approval every time I requested access to the data used in this thesis. I also appreciate the assistance of Miss Sumitra Tangsomworapong and Mrs Busaba Kongpanyakul, staff at the Research Department of the SET, for supporting me in accessing the data online without any issues, and providing me with further data that I requested to fulfil this thesis.

In completing this thesis, I wish to give significant credit to my wife, Mrs Kamonwan Suwankarn, who has always stood beside me and provided massive support and care at every step. I would not have reached this stage in my life without her. I may express my heartfelt gratitude to my ever-supportive and ever-loving family, especially my parents: Mr Paisarn Suwankarn, my dad, who always supported me every step of my life, and Mrs Kumpang Suwankarn, my mom, who has passed away but is still in my heart forever. I would also like to thank my lovely sister, Mrs Sriwilai Boonpeng, her husband, Mr Surin Boonpeng, and her two sons, Mr Suparerk Boonpeng and Mr Pachara Boonpeng, for their support and love.

Furthermore, I would like to express my utmost appreciation to my best friend, Dr. Jinquan Gong, who supported me throughout my PhD journey in the US and the UK. I would also like to thank my friends in Thailand and York for their incredible support throughout my PhD.

Last but not least, I offer my regards to all those who supported me, and contributed directly or indirectly to the completion of this thesis.

Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References. Where individual Chapters were co-authored with other researchers, this is indicated with the necessary specifications in this declaration.

Chapters 1 and 2 are co-authored papers with my supervisors, Dr. Maryam Alhalboni and Prof. Peter Spencer. I contributed to every part of the research, and my co-authors contributed at various points, including revisions and comments. The earlier version of Chapter 2 was presented at the British Accounting and Finance Association (BAFA) Conference at the Ron Cooke Hub on the East Campus, the University of York, on 22nd September 2022.

Chapter 3 is a co-authored paper with Dr Maryam Alhalboni and Prof. Peter Spencer. I contributed to coding and executing panel regression analysis and difference-in-differences (DID), designing methodology and conducting all the empirical analyses. My first co-author, Dr. Maryam Alhalboni, contributed to writing the paper. My second co-author, Prof. Peter Spencer, contributed at various points, including revisions and comments. The earlier version of Chapter 3 was presented at the Centre for Evolution of Global Business and Institutions (CEGBI) PhD Workshop Conference at Church Lane Building, the University of York, on 5th May 2023.

Ruangrong Suwankarn
March 2024, York

Introduction

This thesis comprises an empirical exploration of the Stock Exchange of Thailand (SET) with a focus on addressing key matters within the market microstructure domain. The study aims to contribute to the existing literature in three main areas. The first chapter investigates how turnover and market capitalisation influence the relationship between the price impact of trades and market returns, studying how changes in market returns effect the price impact of trades and how turnover and market capitalisation may influence this relationship. The second chapter delves into the relationship between market conditions and the level of aggressiveness in trading among trader types, investigating how retail, foreign, and institutional traders adjust their order submission aggressiveness dynamically in response to market conditions. This chapter also examines the aggressiveness of individual, institutional, and foreign traders in order submission and studies how market conditions influence this aggressiveness. Finally, the third chapter examines the impact of repeated market-wide circuit breakers (MWCBs) on traders' understanding, in relation to the learning effects of three-times triggering market-wide circuit breakers (MWCBs) occurring in close succession during the first COVID-19 lockdown in March 2020.

This introduction presents an overview of the Thai stock market, outlines the motivations of the three chapters, describes the institutional background of the SET, illustrates the data used in the study, and provides an overview of the thesis's main contributions and structure.

Motivation

▪ Characteristics of the Thai Stock Market

According to the SET report of May 2023, in the Thai stock market, domestic retail traders contributed 29,957 million Baht (39.02%) to the total trading value and foreign traders contributed 34,978 million Baht (45.56%) to the total trading value, so both had a major share. Domestic institutional traders, with a contribution of 5,723 million Baht (7.45%), and brokers, with 6,115 milion Baht (7.96%), played secondary roles. Foreign traders and domestic retail traders dominated the highest daily trading values. This contrasts with developed markets, where institutional traders typically have a significant influence on the daily trading values.

The Thai stock market stands out globally for its distinctive feature – a significant presence of retail traders (Padungsaksawasdi, 2020; Phansatan et al., 2012), setting it apart from other international stock markets. These retail traders employ unique trading strategies that may pose challenges when confronted with an intensified level of trading activity in the Thai stock market. For example, Phansatan et al. (2012) study investor trading behaviour and trade performance in the Thai stock market. They note that domestic individual investors have poor market timing in trading. This poor trading strategy makes them cancel out their gains from profiting in other trading strategies. Also, Paisarn et al. (2021) delve into the trading behaviours of retail traders in the Thai stock market using survey data. They suggest that retail investors in the Thai stock market may not behave reasonably in trading. Therefore, the distinctiveness of individual trading strategies raises concerns about their ability to navigate and respond to the escalating trading environment effectively. Consequently, this limited adaptability to heightened trading activity is anticipated to have a pronounced impact on prices.

Intriguingly, the heightened price impact of elevated trading activity is often associated with less liquid markets. For instance, Ratanabancheun and Saengchote (2017) investigate the increased trading activity at threshold prices, at which the tick size changed, in the Thai stock market, spanning seven years from 2002 to 2008. They point out that there are buy-sell imbalances at threshold prices, and these order imbalances do not allow retail traders to gain profit, but incur excessive trading costs instead. In contrast, our focus is upon investigating whether this relationship holds in the context of the SET 100, the most liquid market in Thailand. This critical inquiry forms the basis of our research question in Chapter 1, as we aim to uncover the association between the price impact of trades and market returns and explore how turnover and market capitalisation affect this association in the unique landscape of the SET 100.

▪ Order Submission Aggressiveness of Different Participants in the Thai Stock Market

In an order-driven market, market participants can submit two types of orders: market orders and limit orders. The market participants who submit a market order are assumed to be impatient traders or urgent investors. The patient and impatient investors are exposed to different types of risk. The impatient investor faces the risk of high price impact whenever the depth available is less than the quantity demanded. When patient investors place a limit order, they face three types of risk: the risk of non-execution, the risk of adverse selection, and the risk of free trading options[1]. Therefore, in addition to deciding upon placing either buy or sell orders, traders need to determine whether to submit market or limit orders (Goettler et al., 2005).

Parlour (1998) finds that before placing either market orders or limit orders, the investors consider the transaction cost, the cost of waiting, and immediate execution. They tend to minimise their transaction cost and balance between the cost of execution and the cost of waiting. The choice between limit and market order is also affected by the market conditions. For example, Goettler et al. (2009) find evidence suggesting that investors' choices are influenced by variations in market volatility. Another important market condition reported in the literature is liquidity (e.g. Biais et al., 1995; Handa and Schwartz, 1996). Moreover, research finds that the spread is negatively related to the likelihood of execution and competition among limit order traders. Foucault et al. (2005) find that the fraction of patient traders and the rate of order arrival are the key factors of the dynamics in the limit order book. Traders place aggressive limit orders when there is a larger proportion of patient traders, or when there is a low rate of order arrival. They also suggest that limit order traders will place more aggressive (passive) orders when the spread is large if patient (impatient) traders are in control of the trading population. In conclusion, traders employ different order submission aggressiveness in response to changes in market conditions.

On the other hand, many studies report that different types of trader use different trading decisions with different levels of order aggressiveness in response to varied market conditions. Chiu et al. (2017) suggest that in the Taiwan index futures market, individual traders are likely

[1] As noted by Liu (2009), free trading option (FTO) is the piking-off risk because writing a conditional free call (put) option is similar to a limit buy (sell) order. Consequently, the arrival of public information influences the option's value.

to employ a more aggressive order submission, whereas foreign institutional traders prefer placing more limited orders than market orders. Park et al. (2019) suggested that the presence of foreigners in the Korean stock market significantly influences the trading behaviours of local individual traders, leading to heightened behavioural biases. Duong et al. (2009) highlight that diverse market conditions influence the distinction in trading decisions of institutional and individual investors.

These studies provided insights into the trading decisions of two types of trader depending on the market conditions. However, the question regarding how three types of trader, namely institutional, foreign, and individual traders, dynamically adjust their order submission aggressiveness in response to diverse market factors, especially in the Thai stock market, is unexplored. Therefore, variations in trading decisions based on order submission aggressiveness among different types of trader in the Thai stock market are investigated in Chapter 2.

▪ Market-wide Circuit Breakers (MWCBs) in the Thai Stock Market During COVID-19

Market-wide circuit breakers (MWCBs) are one of the trading regulations used by stock trading venues worldwide. MWCBs are regulatory measures in stock exchanges to halt short-term trading, aiming to mitigate the panic selling of market participants and alleviate high volatility. They are triggered automatically to stop trading when the prices are equal to or lower than a threshold set by the markets, such as -7% or -10% in an intraday movement. A trading halt, which arises after triggering MWCB for a short period around 15 or 30 minutes and then resuming trading, is a regulatory measure for a temporary trading suspension in a particular asset to remedy order imbalance, or due to concern about a negative or positive news announcement that is either detrimental or beneficial to market participants who buy assets before or after the announcement.

There is a mixed finding on the effectiveness of MWCBs. From an optimistic viewpoint, MWCBs can help reduce market volatility (e.g. Kyle, 1988; Santoni and Liu, 1993; Kim et al., 2013; Goldstein, 2015), alleviate delayed price discovery (Engelen and Kabir, 2006; Hausser et al., 2006; Madura et al., 2006), enhance trading volumes (Greenwald and Stein, 1991; Ferris et al., 1992; Corwin and Lipson, 2000; Li and Yao, 2021; Lin et al., 2022), and lead to more informative stock prices (e.g. Lin et al., 2022). However, from a pessimistic viewpoint, MWCBs increase volatility after resuming trading (Kryaznowski and Nemiroff, 2001; Bildik and Gulay, 2006; Danisoglu and Guner, 2016) and cause illiquidity risk or delayed price discovery (Corwin and Lipson, 2000; Wong et al., 2009).

There was no MWCB for almost ten years until it was triggered worldwide again during the first COVID-19 lockdowns in March 2020. In Thailand, the sharp selloff resulted in a series of interventions during March 2020 because the SET aimed to calm the market participants in the Thai stock market. The first and the second arose consecutively on the 12th and 13th of March 2020, with 30-minute trading halts after the SET index fell by 10% due to the massive decline in the European and US stock markets. The SET announced a temporary change of the short-selling rule on 13 March 2020, a narrower range of the SET index movement for triggering future MWCBs, and a narrower range of the limit up-limit down rule on 18 March 2020. Eventually, the third MWCB was triggered by the SET.

The scenario that occurred within the Thai stock market, whereby MWCBs were triggered three times in close succession by a single exchange within one month in March 2020 is rare. In particular, the third trigger of MWCB by the SET risked losing credibility if this trigger failed to calm financial market participants in the Thai stock market. Consequently, the learning effects upon traders in the Thai stock market are crucial in providing insights into the efficiency of the collaboration between revised regulations regarding the MWCBs and the adaptation of traders via learning effects in response to MWCBs. Therefore, Chapter 3 will study how traders modify their responses to MWCBs depending on their earlier experience of the previous two MWCBs within a series of applications.

Contribution

This thesis investigates the empirical characteristics of market dynamics and trading strategies in the Stock Exchange of Thailand (SET).

Chapter 1 contributes to the literature by investigating how turnover and market capitalisation influence the relationship between market returns and the price impact of trades in the context of the SET100 index. The results indicate there is low information asymmetry, low transaction cost, and high market liquidity among the stocks listed in the SET100 index, because the 100 largest market-capitalisation listed firms constitute the SET100 index in the Thai stock market. The findings show that trades have a decreased price impact when favourable market conditions arise in the Thai stock market, such as a bullish market with positive price trends and/or relatively high market capitalisation. The results show that the price impact of trades increases when the level of turnover is higher. The results also report that an increase in the bid-ask spread is caused by an increasing level of turnover, exhibiting the shallower market depth. The answer to this relationship is that the Thai stock market has a high percentage of individual investors.

Another main contribution of this thesis is to investigate the trading submission strategies of different types of traders, examining how they alter their order submission aggressiveness in response to market conditions. These investigations are conducted in Chapter 2. The findings indicate that foreign traders are the most strategic participants in employing order submission aggressiveness, as evidenced by their significant activity in cancelling existing orders. Their high willingness to cancel orders underscores their sensitivity to non-execution costs, prompting them to cancel and resubmit orders to ensure execution. Their sensitivity to non-execution costs can also be found when the bid-ask spread increases, and the market experiences a reduction in liquidity. However, the results show that they are cautious about the picking-off risks, as reflected in their tendency to step back and submit passive orders if there is heightened volatility in the market.

The final novel contribution of this thesis is in Chapter 3, which explores the learning effect for traders of the occurrence of three market-wide circuit breakers (MWCBs) triggered by the SET in the same month, March 2020, during the first COVID-19 lockdown. The present study is the first analysis of the separate learning effects of each MWCB within three consecutive MWCBs in close succession, as triggered by the SET to restore normal market function. By comparing the effectiveness of the latter MWCB relative to the previous MWCB, the results help provide practical policies to manage the sequence of triggering MWCBs. The results also directly inform the trade-off between the repeated uses of MWCBs and the potential benefits, including the associated costs and risks. Although there are several works of literature that investigate the effectiveness of a one-time MWCB, these studies do not investigate learning effects in traders in relation to the repeated use of MWCBs. Finally, the learning effects that this study aims to identify have the potential to help reconcile the literature solely studying the effectiveness of MWCBs with the learning effects. The results in Chapter 3 find consistent evidence across several indicators regarding market quality that even though the first two MWCBs failed to restore market quality, triggering the third MWCB generated dissimilar responses from market participants, enabling the SET to curb heightened volatility. This learning effect is highly relevant to the effectiveness of MWCBs when used serially.

Background

▪ Participants

The participants in the capital market can be classified into two categories: traders and intermediaries. Traders include regular customers seeking to trade their own financial assets. Customers who engage in financial asset transactions are called either individual investors or institutional investors if they are, for example, pension funds or mutual funds. Traders also include dealers who are substantial professional traders, who possess the ability to supply liquidity in the market.

Rust and Hall (2003) define the intermediaries as two types: middlemen (dealers/brokers) and market markers (specialists). Brokers carry out orders placed by customers. They act strictly as agents for investors and do not incur any risk except order costs (Stoll, 1978). By contrast, dealers provide immediacy more cheaply than investors. They can be viewed as any investor based on the opportunity they see. In the dealer business, there are fixed costs like office, meaning that not everyone can be a dealer (Stoll, 1978). Specialists are responsible for two functions: brokers and dealers (Conroy and Winkler, 1981). Their first function is to be brokers by matching orders for others. Their second function is to be dealers by trading for their own accounts. Market makers post the bid and ask prices the public can observe (Rust and Hall, 2003), serving as liquidity suppliers.[2] Rust and Hall (2003) also compare market makers (also known as specialists) and middlemen (also known as dealers or brokers) as follows. Market makers are typically members of, or own, the exchange, whereas dealers or brokers trade at individually negotiated prices. Madhavan (2000) notes that market makers quote the bid and ask prices at which they have a willingness to buy or sell, respectively. The spread of market maker is the difference between their posted bid and ask prices. Market makers also occupy a passive role by adjusting the bid-ask spread in response to changes in market conditions. Stoll (1985) also notes that market makers like NYSE specialists confront the competition from floor traders, dealers, limit orders, and other exchanges. Regarding two types of exchanges: an order-driven market and a quote-driven market (or a dealer market), there is no dealer intermediation in an order-driven market, whereas market makers take the opposite side of every transaction in the quote-driven market (Madhavan, 2000).

[2] In the case of a quote-driven market, dealers are also called market makers.

▪ Markets

Generally, the world's stock markets are categorised into two main types: a quote-driven market (or dealer market) and an order-driven market (or limit order market) (Wuyts, 2007). The most important character of a quote-driven market, like the bond market in MTS and forex markets, is that the liquidity providers or suppliers are the market makers who submit a bid and ask quote at which market participants can trade.[3] However, there is no market maker in an order-driven market like the Deutsche Boerse and the Paris Bourse; market participants trade directly in an order-driven market. Market participants can be liquidity demanders by submitting market orders or liquidity suppliers by placing limit orders. Also, an order-driven market can be categorised into two subordinate types of auction markets: a call auction market and a continuous auction market. A call auction market occurs at a specific time, such as at the opening and closing of the market. Market participants can submit their orders to be executed at a single clearing price. A continuous auction market like Euronext, the Toronto Stock Exchange (TSX), or ECNs is where market participants can trade with each other based upon the market's trading rules, like the price and time priority rule.[4]

▪ Stock Exchange of Thailand (SET)

The Stock Exchange of Thailand (SET) functions within the regulatory framework launched by the Securities and Exchange Act (SEA), replacing the SET Act (1974) in 1992. The SEA established the Securities and Exchange Commission (SEC) to oversee the entire national securities industry. As per the SEA, the SET has several key responsibilities, including operating as a marketplace for trading listed securities, providing effective systems for securities trading, conducting related businesses such as clearing, and carrying out other approved activities under SEC supervision.

The SET is a non-profit organisation that began to trade on 30 April 1975. It is the main exchange in Thailand without linking to other exchanges for cross-listing purposes. The board

[3] MTS is part of the London Stock Exchange Group (LSEG) and is one of Europe’s leading facilitators of electronic fixed income trading platforms, trading European government bonds, quasi-government bonds, corporate bonds, covered bonds and repo (London Stock Exchange, 2023; MTS market, 2023).

[4] Euronext is the Europe’s largest stock exchange and the sixth largest in the world. It operates markets in Amsterdam, Brussels, London, Lisbon, Dublin, Oslo, and Paris (Euronext, 2023). ECNs are a type of alternative trading system (ATS) that trade listed stocks and other exchange-traded products (The U.S. SEC, 2020).

of directors of the SET is composed of eleven people: (i) five are appointed by the SEC, (ii) five are elected by the members of the SET, like brokers, and (iii) the board of directors has a right to appoint the president of the SET and let the president be an ex-officio of the board. The board of directors also formulates the policies of the exchange and supervises its operation. Although the board of directors has a right to prescribe certain rules and regulations regarding the exchange, the SEC must approve these before they take effect.

The SET's market capitalisation to GDP ratio consistently expanded following the 1997 Asian financial crisis originating in Thailand. By 2022, this ratio reached 121%, indicating the significant growth of the Thai stock market (SET, 2023a). In the period between 2012 and 2022, the trading value of the SET consistently exceeded that of other countries in the ASEAN region, with a daily average trading value of 76,773 million Baht and an average yearly growth of 23.30% (CAGR).

The 50 and 100 largest companies by market capitalisation, out of approximately 627 listed companies in 2023, had a substantial impact on the market dynamics, representing around 68% and 78%, respectively. These top 100 market-cap listed firms generally constitute the SET100 index, which forms the dataset utilised in our study.

▪ SET Trading Systems

The SET trading system is fully computerised. The SET operated the Automated System for the Stock Exchange of Thailand (ASSET) in April 1991. The ASSET enabled trading with efficiency, equitability and fluidity. Later, the SET upgraded to a new trading system called Advanced Resilience Matching System (ARMS) in August 2008 in response to rapidly changing business demand, and to follow the trend in the global financial market. The main features of the ARMS are higher risk management efficiency and improvement of system redundancy.

SET CONNECT was the latest trading system introduced by the Stock Exchange of Thailand (SET) on 3 September 2012. The purpose of introducing a new trading system was to cope with the expansion of the Thai capital market. The main benefits of this new trading system are increasing trading efficiency, easy access to the Thai stock market with international standard protocol, and covering new products and other trading innovations.

This trading system can provide two approaches. The first one is automatic order matching trading (AOM), which performs the order-matching process depending on price and time priority without human intervention. In this system, the SET CONNECT queues the submitted orders and arranges them according to the price-then-time priority. This procedure means submitted orders are grouped according to price, with the best price being the first in the queue. Then, submitted orders are arranged according to time within each price group. There are two methods of matching: continuous order matching and auction matching. The procedure of continuous order matching operates during the regular trading session, and the SET CONNECT continues matching the buy and sell in the queue. The auction matching method is employed during the time of opening and closing of the trading days. In this method, traders place their orders to be queued for matching at a specified time near the open or close time. The SET CONNECT will consequently match all trades at a single price, which is the price of the largest trading size submitted for each stock. The types of securities allowed to trade via the AOM are common stocks, preferred stocks, warrants and unit trusts, stocks registered under the names of foreigners, and odd lots. The second essential trading system is the Trade Report (TR), previously known as Put-Through (PT). In this system, brokers can advertise their buy and sell interest by announcing bid or ask prices. The execution will be agreed directly with each other, either on behalf of themselves or their clients. Since dealt securities prices are adjustable during the negotiation, the effective executed prices may not be similar to advertised securities prices. In addtion, they may not follow the rules of spread price proposed by the SET. Whenever the negotiations are concluded, dealers or brokers need to submit the details of the deals to the SET CONNECT to be recorded. The trades allowed to use the TR system are transactions for big-lot trading with at least one million units of traded securities or at least three million Baht, for off-hours trading, and for buy-in.

From 8 May 2023 onwards, the SET and Thailand Futures Exchange (TFEX) implemented the New Trading System by collaborating with NASDAQ to develop it with the latest technologies and innovations according to global trends. The two main features of this new trading system are accommodating a substantial increase in transactions and providing more diverse global products to domestic and foreign investors. For example, the new trading system introduced orders and deals timestamps at the nanosecond level to be consistent with most exchanges worldwide. Also, it increases the dissemination of bid-ask price depth of trading securities from a five price level to a ten price level, to help investors monitor data more deeply.

▪ Trading Hours

There are three main trading sessions: (i) the morning trading session runs from 10:00 to 12:30, (ii) the afternoon trading session runs from 14:30 to 16:30, and (iii) the off-hours trading session runs from 16:30 to 17:00. Morning trading sessions have random opening times between 09:55 and 10:00, but traders can submit their orders starting from 9:30 without execution until the morning random opening times are triggered. After the morning random opening time, the morning trading sessions have continuous trading until 12:30. Afternoon trading sessions start at 14:00 and have afternoon random opening times between 14:25 and 14:30. The afternoon trading sessions extend from a randomly determined opening time until 16:30. During the brief period between 16:30 and 16:35, traders are permitted to submit orders, but these orders remain pending execution until the SET declares the closing price between 16:35 and 16:40. Subsequently, all outstanding orders are matched with this closing price to conclude the trading session.

After the regular morning and afternoon trading sessions are closed, off-hours trading sessions are the extra trading period (SET, 2024a). Investors who engage in off-hours trading do so for various reasons. They may prefer trading with just a few financial participants in the Thai stock market, or their schedules may require them to do so. They may take positions in response to news that arises after the regular trading session. This extended trading time helps investors, particularly institutions and foreigners, adjust their positions, modify transaction errors, and cover the transactions executed in the regular trading session. Since the random closing times happen from 16:35 to 16:40, off-hours trading will start at these random closing times until 17:00.

According to the SET, only three trade reports are allowed for off-hour trading: the trade report for off-hour, big lot, and foreign. They are recorded following specified rules. First, the trade report for off-hours states that each transaction needs fewer than 1 million shares and a value of less than THB 3 million. The price used is that trading day's closing price or volume weighted average price (VWAP). However, the last closing price will be employed if both are unavailable. Second, the trade report for big lot is that each transaction must trade at least 1 million shares or at least THB 3 million, with no tick size rule requirement. The price limit is +/-30% of local shares' closing price on the prior day. This trade report can be both one-firm or two-firm trade, and advertisement via the trading system is permitted. Third, the trade report for foreign is that each transaction must have a volume of less than 1 million shares and a value of less than 3 million Baht. The price limit is +/-60% of local shares' previous daily closing price. Both one-firm and two-firm trade reports are allowed, and the SET allows advertising through its trading system.

- **The Rules of Price Variations**

A. Tick Size Regulation

The SET has established rules for price movement, known as the tick size, in securities trading.[5] The tick size varies based on different market price levels, as shown in Table 0.1.

Table 0.1: Price Spread - Tick Size

Price Range (THB)	Tick Size (THB)
0.01 – less than 2.00	0.01
2.00 – less than 5.00	0.02
5.00 – less than 10.00	0.05
10.00 – less than 25.00	0.10
25.00 – less than 100.00	0.25
100.00 – less than 200.00	0.50
200.00 – less than 400.00	1.00
greater than 400.00	2.00

Source: The Stock Exchange of Thailand (SET)
Notes: This concept is officially applied to all listed stocks traded in the Stock Exchange of Thailand (SET) effective 30 March 2009 onwards.

The tick size changes by at least THB 0.01 when the stock price is less than 2.00 Thai Baht, but stock cannot be traded in the SET at a price of less than THB 0.01. Suppose the stock price equals or exceeds 2.00 Thai Baht, but is less than THB 5.00. In that case, the tick sizes will change from 0.01 to 0.02 at the minimum tick size that can be traded, meaning that, for example, 0.02, 0.04, and 0.06 are the possible tick sizes that can be traded, or divisible by 0.02, but 0.03, 0.05 and 0.07 are examples of disallowed tick sizes. When the stock price ranges between THB 5.00 and not exceeding THB 10.00, the stock is traded at the minimum tick size of 0.05 Thai Baht (or divisible by 0.05) and changes to THB 0.10, or divisible by 0.10, when the stock price ranges between THB 10.00 and less than THB 25.00. The tick sizes rule will be determined at a minimum of THB 0.25, or divisible by 0.25, to trade for stock with a range price from THB 25.00 to less than 100.00 Thai Baht. From THB 100.00 to less than THB 200.00, stock price levels are traded with the tick size at the variation of at least 0.50 Thai Baht

[5] However, unit trust and exchange-traded funds (ETFs) are traded not by following the tick size rule specified in Table 1.1, but their tick size is 0.01 Baht.

(or divisible by 0.50). Suppose the stock price continues going up until it equals 200.00 Thai Baht and exceeds but is less than 400.00 Thai Baht. In that case, the SET will impose the tick size at a minimum of THB 1.00 or divisible by 1.00. When the stock price rises exponentially to equal or exceed 400.00 Thai Baht, the minimum tick size that the traders can trade is THB 2.00, or divisible by 2.00.

B. Floor and Ceiling Limit Rules (or the Limit Up-Limit Down: LULD) and Market-wide Circuit Breakers (MWCBs)

The SET determines a limit for the price movement of traded securities. For local trades, the securities prices can vary within 30 per cent of the securities' previous daily closing price. By contrast, foreign securities have a price limit within a range of 60 per cent of the previous closing price.

In addition to LULD, the SET also implemented market-wide circuit breakers (MWCBs) to curb excessive volatility in the market that may lead to panic among investors (SET, 2023b). The MWCB proposed by the SET, effective on 18 March 2020, functions in three stages. In the first stage, if the SET index falls by 8% from the previous closing day, all transactions traded in listed securities will be halted for 30 minutes, and then all trading will resume. In the second stage, all trading in listed securities will be halted for 30 minutes when the SET index falls by 15% from the previous day's close. After the 30-minute halted period, all trading in listed securities will be resumed. In the third stage, if the SET index falls by 20% compared to the previous closing day, all trading in listed securities will be halted for one hour, and then trading will be resumed. After the third stage, the SET will continue matching orders until the close of the market session, and there will be no more halted market.

Data

As the same dataset is utilised throughout the chapters of this thesis, a general overview will be provided here to prevent redundancy. Additional details specific to the data used in each chapter will be presented within the corresponding chapters.

We collected tick-by-tick trading data directly from the SET trading dataset. The dataset consists of two files: the ORDER and DEAL files. The ORDER file contains information regarding order submissions with different trade IDs, time stamps, security symbols, the type of investors, the stock price, the volume and value of each order, and the trade direction (buy or sell). The DEAL file provides information regarding executed transactions with different IDs of sellers and buyers, deal time, deal date, deal volume, deal price, deal status, the type of investors on either the buy or sell side, and security symbol. The ORDER and DEAL files are merged to join them based on a unique order submissions trade ID, time stamps, security symbols, the type of investor, the stock price, the volume and value of each order, and the trade direction. After merging, the data will be a single merged data readily employed for the research. However, before conducting our research, this single merged data set will be filtered on the stocks listed in the SET100 index, and the time horizon will be set from tick-by-tick to a one-minute time interval.

Overview and Structure of the Thesis

The remainder of the thesis is organised as follows. Chapter 1 examines the influence of turnover and market capitalisation on the relationship between the price impact of trades and market returns. It also investigates the effect of the heightened trading activity on market liquidity and price discovery. The study focuses on the unique context of the SET100 index, consisting of the 100 most liquid and largest market capitalisation listed companies. Chapter 2 examines the differences in order submission aggressiveness of individual, institutional, and foreign traders and how this order submission aggressiveness changes in response to different market factors within the Thai stock market. Chapter 3 studies the learning effects of serial market-wide circuit breakers (MWCBs) on traders. The Conclusion provides a summary report of the key findings of the thesis.

Chapter 1

The Role of Heightened Trading Activity in Liquidity, Price Discovery, and Price Impact within the Thai Stock Market: An Empirical Analysis

1.1 Introduction

At present, most stock markets worldwide are of two types: pure electronics limit order markets and quote markets (Parlour and Seppi, 2008). Stock venues and investors have enthusiastically embraced technological advancements in electronic trading. In such instances, investors demonstrate competence in gathering and digesting investment information, so as to decide on their trades with increased frequency and pace. In Thailand, this tendency led the Stock Exchange of Thailand (SET) to establish the new SET CONNECT trading system in 2012. The SET continued providing new services, like co-location services with lower latency, to convince investors who prefer speed in their trading.

The profound impact of heightened trading activity on the overall market quality has raised questions worldwide, including in Thailand. One optimistic viewpoint asserts that increased trading activity enhances liquidity (Hendershott et al., 2011; Hagstromer et al., 2014; Jarnecic and Snape, 2014), improves price discovery (Conrad et al., 2015), reduces market volatility (Aggarwal and Thomas, 2014), and helps investors to rebalance their trading positions and portfolios in a timely and accurate fashion as the information arrives (Linton and Mahmoodzadeh, 2018). On the contrary, a pessimistic perspective argues that the heightened trading activity leads to reduced intraday liquidity, posing challenges for intraday price discovery (Lee, 2015). Additionally, price impact is indirectly referred to as the measurement of illiquidity (Kyle, 1985). Illiquidity is positively associated with stock excess returns. The effects of illiquidity are more substantial on the returns of portfolios with small-firm stocks, indicating traders need a premium or excess return on higher illiquidity risk on small-firm stocks, which is why the larger-firm stocks are more attractive to trade than small-firm counterparts (Amihud, 2002; Healy and Palepu, 2021). Nevertheless, the question of the potential influence of market returns on trading activity and the impact of trading activity on price impact remains unanswered.

There is a belief that turnover and market capitalisation could influence the relationship between price impact and market returns. While some studies assert that higher trade turnover leads to lower price impacts (Lakonishock et al., 1992; Sun and Ibikunle, 2017), the opposite viewpoint argues that higher trade turnover is related to a stronger price momentum (Lee and Swanminathon, 2000) and causes higher price impacts (Lee and Swanminathon, 2000; Chiyachantana et al., 2004). The price impact from trades on larger firms will be lower due to a reduced spread in higher capitalisation firms (Bouchaud et al., 2009). None of these studies have examined the potential influence of turnover and market capitalisation in the association between price impact and market returns.

Therefore, this study will examine the relationship between market returns and the price impact of trades and explore how turnover and market capitalisation result in this relationship. This study also investigates the effect of heightened trading activity on intraday liquidity and price discovery. This study's findings aim to help policymakers consider practical regulations during increased trading activity and help investors become aware of and consider the impact of heightened trading activity on their trades.

This study collects the trading data sample from January to June 2019 in the Stock Exchange of Thailand (SET), consisting of 98 stocks comprising the SET100 Index. Different spread measures will be analysed, i.e., the quoted spread, the effective spread, the realised spread, and the price impact. Panel regression analysis will be used to examine the intraday liquidity of the Thai stock market. Vector autoregression (VAR), impulse response function (IRF), and cumulative impulse response functions (CIRF) will be employed to investigate intraday price discovery in the Stock Exchange of Thailand (SET). Studies will be carried out on the overall stocks, and these will be categorised into four quartiles with different market capitalisations to check their differences.

Aligned with Hasbrouck's studies (1991a, 1991b), in our unconditional analysis, we observed that entities listed in the SET100 index demonstrated a diminished degree of information asymmetry, transaction costs, and price impact of trade when compared to smaller-capitalisation ones listed outside the SET100 index. This phenomenon is explained by reduced information asymmetry and increased liquidity within high-capitalised firms, a characteristic of the SET100 constituents, as supported by the research of Healy and Palepu (2021).

However, an intriguing phenomenon comes to light when examining the interplay between turnover levels (or market returns) and the impact of trades on stock prices. The results show that an escalation in the turnover volume or market returns correlates with a heightened impact of trades on prices. Notably, the Stock Exchange of Thailand (SET) is marked by a substantial presence of individual traders. The increased impact can be attributed to the inherent challenges faced by individual traders in managing high turnover and contributing to liquidity, reflecting higher illiquidity risk. Our results provide additional insight into this phenomenon. As the level of turnover volume increases, there is an increase in the bid-ask spread, suggesting a shallow market depth. This corroborates the notion that the heightened impact of trades on prices is associated with the presence of individual traders who struggle to cope with the increased level of transaction volume, leading to a decrease in market depth, as reflected in the widening bid-ask spread.

The remainder of this paper is organised as follows. Section 1.2 reviews the literature concerning the relationships between (i) price impact and information asymmetry, (ii) price impact and turnover, (iii) price impact and returns, (iv) price impact, price level and price trend, and (v) previous studies of factors affecting the stock prices in the Stock Exchange of Thailand (SET). Section 1.3 gives information regarding the methodology: (i) measures of intraday liquidity, (ii) measures of intraday price discovery, and (iii) the effect of market-wide and stock-level factors on trade via different spread measures. In section 1.4, the data collection will be outlined. Section 1.5 provides the results regarding the descriptive statistics and the main results. Finally, we conclude our study in section 1.6.

1.2 Literature Review

1.2.1 Price Impact and Information Asymmetry

Information asymmetry or asymmetric information arises when a party has better information and therefore gains an advantage. Price movements can be significantly interpreted in the financial markets as information imbalances, allowing better-informed investors to obtain better returns than their uninformed counterparts. Saar (2001) develops a theoretical model investigating the permanent price impact asymmetry phenomenon between block trades initiating buy and sell orders. He gives two reasons to explain the permanent price impact of block trades. The first is inelastic demand and supply curves, and the second is the information effects. His paper helps us to gain insight into the contributing factors that cause the persistent price impact. Healy and Palepu (2001) review the empirical literature regarding disclosure regulation, information intermediaries, and corporate disclosure's determinants and economic consequences. They highlight the relationship between information asymmetry, corporate disclosure, and capital markets. They find that reducing information asymmetry via improved corporate disclosure practices can result in more efficient price movements in the capital markets. These findings also suggest that an increase in transparency and the availability of information can help mitigate the effect of the price impact of information asymmetry on stock price movement. Two main reasons can explain these findings. The first is that large market capitalisation firms are more likely to disclose more information publicly on corporate disclosures, because they will benefit most from reduced information asymmetry (Diamond and Verrechia, 1991). They act this way to attract large investors, like institutional investors, leading to increased liquidity and a decreased price impact in relation to their securities. The second reason is that institutional investors also demand large-cap companies with high institutional ownership because they are able to demonstrate greater firm transparency by showing more managerial and analyst public information production, such as voluntary disclosure via management forecast, to minimise their transaction and monitoring costs (Boone and White, 2015). As a result, there is a reduction in information asymmetry and an increase in liquidity in these large-cap stocks. Easley and O'Hara (2004) investigate how information affects a firm's cost of capital. Their results show evidence that both the quantity and quality of information affect asset prices. These findings also indicate that information asymmetry can impact price movements by affecting the cost of capital and subsequently influencing the valuation of assets or securities. Sun and Ibikunle (2017) find that the permanent price impact of block trades is higher when the level of informed trading in a stock is larger. The implications of their findings indicate that informed trading aids the price discovery process for stocks with lower transparency.

In brief, the literature indicates that information asymmetry is crucial for price impact and stock price movement. The quality of information, such as availability, transparency, and the level of information disclosure, can impact the level of information asymmetry and stock price impact.

1.2.2 Price Impact and Turnover

Some studies have delved into the relationship between price impact and trade turnover. Sun and Ibikunle (2017) examine the intraday price impact of block trades regarding the presence of informed trading using high-frequency data from the London Stock Exchange (LSE). They find that the number of informed trades is positively associated with the number of block trades. They also find that informed trading is positively (negatively) related to the permanent price impact of block purchases (sales), which indicates the existence of impounded private information through block trades. They suggest that the gradual incorporation of private information into prices arose despite heightened trading frequency, indicating that the frequency of trading may not necessarily dampen the impact of block trades on prices. They also find that firms with low trading transparency exhibit a stronger impact on private information incorporation than their counterparts with high trading transparency. Price discovery is facilitated by informed trading in the same direction as the permanent price impact of block trades in both sales and purchases.

Lakonishok et al. (1992) evaluate the effect of trading by institutional investors on stock prices, focusing on two aspects of trading patterns: herding and positive feedback. These two trading patterns commonly inform the argument that institutional investors make stock prices destabilising. They find that institutions follow a broad range of styles and strategies that help offset each other without producing a large impact on prices. This broad diversity of institutions helps stabilise asset prices and prevent herding in equilibrium. They also suggest institutional investors may appear to follow herding patterns if they all react promptly to the same fundamental information. If so, they will facilitate the market more efficiently by escalating the price adjustments to new fundamentals. These findings indicate that higher trade turnover leads to increased price impact if institutions all react to the same fundamental information promptly.

On the other hand, Lee and Swanminathon (2000) investigate an essential link between momentum and value strategies provided by past trading volume. They find that past trading can predict the magnitude and persistence of price momentum, suggesting a positive relationship between price momentum and trade turnover. Chiyachantana et al. (2004) study institutional trading behaviour and the price impact of institutional trading in international stocks. They find that the price impact asymmetry between block trades' buying and selling depends on the underlying market condition. In bullish markets, a larger price impact arises on the buying side of institutional investors rather than on the selling side. By contrast, institutional sales have a bigger price impact in bearish markets than their purchases. They also find that price impact varies depending upon firm-specific factors. In particular, a negative correlation exists between price impact and a stock's market capitalisation and price level. Price impact also varies with order characteristics and country-specific characteristics. Spierdijk (2004) examines the price impact of trades and the relation of this to the trading intensity using high-frequency data. This study finds that significant causality exists between trade characteristics and trading intensity. Large trades escalate the trading speed, while large returns reduce trading intensity. The larger price impact of trade arises from the higher trading intensity, indicating that there are more informed trades in frequent trading periods.

1.2.3 Price Impact and Returns

The price impact can be indirectly measured as illiquidity (Kyle, 1985; Chiang and Zheng, 2015). Liquidity is one of the crucial market conditions for traders when trading stock (Amihud et al., 2015). If the risk of illiquidity arises during trading stocks, traders will demand a return premium to compensate for this risk (Amihud and Mendelson, 1986; Amihud et al., 2015). A novel paper proposed by Amihud (2002) shows the positive relationship between illiquidity and expected returns in stock. He studies this relationship in the U.S. market. He finds that the excess return of stock, referred to as risk premium, compensates for the higher illiquidity of stocks. Amihud et al. (2015) and Chiang and Zheng (2015) expand the data, focusing only on the U.S. market to the international markets. Their findings still support the evidence that the expected returns of assets are decreasing in liquidity.

1.2.4 Price Impact, Price Level and Price Trend

Some studies explore the relationship between price impact, price level, and price trends. Saar (2001) investigates the price impact asymmetry in block trades and finds that block trades exhibit stronger positive asymmetry during periods of poor price performance or little price appreciation. Block trades after a price run-up exhibit less or even negative asymmetry. Chiyachantana et al. (2004) find a negative relationship between price impact and price level of stocks, suggesting that a higher price impact of trades occurs for stocks with lower prices than those with higher prices.

1.2.5 Previous Studies of Factors Affecting the Stock Prices in the Stock Exchange of Thailand (SET)

Several studies investigate the impact of various determinants on stock prices in the Thai stock market. Panyagometh (2020) studies the impact of the COVID-19 pandemic on the SET in terms of stock price reactions and market volatility, using 46 listed equities in the SET. His findings indicate that most stocks in the SET were adversely affected by this pandemic, and market volatility was significantly higher. These findings also provide more understanding of external factors or events that substantially affected stock prices. Another study by Pojanavatee (2020) examines whether the four-factor model explained variation in the SET's expected returns of listed equities. This study considers market factors such as size, the book-to-market ratio, the market beta, and stock liquidity. The findings indicate that these factors significantly impact stock prices. This study suggest that these factors play a crucial role in determining the rate of returns on the SET.

Some studies also examined the price impact of different trading types, trading costs, information asymmetry, and information disclosure of listed firms in the SET. Jenwittayaroje et al. (2015) examine trading costs incurred by traders who submitted the market orders and traders who placed limit orders. They also examine the relationship between trading cost and stock/order characteristics. Their findings suggest a positive relationship between the total trading cost and order size and stock price volatility, and a negative association between the total trading cost and firm size, stock price, and stock liquidity. The higher price impact of market orders comes from large orders, small firm stocks, low-priced stocks, stocks with high volatility, and stocks with low liquidity. Chiyachantana et al. (2013) investigate the relationship between information disclosure, firm characteristics, and information asymmetry. They find that increasing corporate disclosure and transparency reduces information asymmetry between informed and uninformed traders. They also find a strong relationship between firm characteristics and information disclosure level. Their findings also suggest that low relative bid-ask spread and high share turnover result from high corporate transparency and disclosure of listed firms in the SET.

However, none of these studies aims to investigate the influence of turnover and market capitalisation on the relationship between the price impact of trade activity and market returns, as the present study does.

1.3 The Methodology

The study aims to identify the effect of heightened trading activity on stocks in the Stock Exchange of Thailand (SET) on intraday liquidity, price discovery, and price impact (information asymmetry or adverse selection). It also compares different market capitalisation groups of stocks to their counterparts. This study uses three methodologies to measure intraday liquidity, intraday price discovery, and the effect of market-wide and stock-level factors on trade via different spread measures.

1.3.1 Measures of Intraday Liquidity

This intraday liquidity measure is put forward by Lee and Ready (1991), Bessembinder (2003), Boehmer, Saar, and Yu (2005), Hendershott, Jones, and Menkveld (2011), Riordan and Storkenmaier (2012), and Malinova, Park, and Riordan (2018). We use a wide range of proxies for measuring intraday liquidity. The intraday liquidity measure includes the quoted spread, the effective spreads, the realised spreads, and the price impact of trade at the one-minute horizon. The equations below are half-spreads compared to stock price. They are also reported in basis points (bps).

The quote midpoint is the most common estimator used in market microstructure to evaluate liquidity and price discovery (Hasbrouck, 1995; Hasbrouck, 2003; Hagstromer, 2019). The quote midpoint measure needs less effort to be interpreted by market participants due to its real-time calculation in the form of an arithmetic average of the bid and ask prices (Hagstromer, 2019). Especially in a purely order-driven market, the submitted orders will be valid throughout the day, and the submitted orders will be cancelled if market participants cancel them or leave them until the market closes that day. The system of the stock market will cancel their orders automatically. This environment leads to continuous quote midpoint observations during trading hours (Hagstromer, 2019). The quote midpoint, m_{it}, is defined as

$$m_{it} = \left[\frac{p_{it}^{A} + p_{it}^{B}}{2}\right] \tag{1.1}$$

Where p_{it}^{A} = the ask price in the limit order book for stock i at time t in minute

p_{it}^{B} = the bid price in the limit order book for stock i at time t in minute

The quoted spread is the most common measure to estimate trading costs (Riordan and Storkenmaier, 2012). In this study, the quoted spread is calculated through the limit order book submitted by all market participants in the SET. The quoted spread is defined as

$$\mathrm{Qspread}_{it} = \left[\frac{\left(\frac{p_{it}^{A} - p_{it}^{B}}{m_{it}}\right)}{2}\right] \tag{1.2}$$

Where m_{it} = the quote midpoint showing at the time of the trade in a minute

The effective spread is the spread or trading cost paid by liquidity demanders who would like to execute immediately on the opposite side of the submitted limit order recorded in the order book, and also consists of the cost of adverse selection (or price impact) as will be mentioned in equation (1.5). We can show their relationship as the formula: the effective spread = the realised spread + the price impact.

The effective spread can also capture some institutional features of a market, such as market depth and hidden liquidity (Riordan and Storkenmaier, 2012). The effective spread, $\mathrm{Espread}_{it}$, is calculated as follows:

$$\mathrm{Espread}_{it} = \left[d_{it} \times \left(\frac{p_{it}^{E} - m_{it}}{m_{it}}\right)\right] \tag{1.3}$$

Where d_{it} = the trade direction indicator (+1 if a market buy order and -1 if a market sell order)

p_{it}^{E} = the execution price in the limit order book for stock i at time t in minute

The realised spread estimates liquidity suppliers' revenues, independent of the costs of the adverse selection imposed by informed traders on uninformed traders (Bessembinder and Kaufman, 1997). In other words, these liquidity suppliers are the uninformed traders who do not suffer the consequences of adverse selection influenced by the informed traders (Bessembinder and Kaufman 1997) by assuming that the liquidity suppliers can close their position at the quote midpoint one minute after the trade. The realised spread, $\mathrm{Rspread}_{it}$, is calculated with the quote midpoint one minute after the trade, meaning that x is equivalent to 1 in the equation (1.4) as follows:

$$\mathrm{Rspread}_{\mathrm{it}} = \left[\mathrm{d}_{\mathrm{it}} \times \left(\frac{\mathrm{p}_{\mathrm{it}}^{\mathrm{E}} - \mathrm{m}_{\mathrm{it+x}}}{\mathrm{m}_{\mathrm{it}}}\right)\right] \tag{1.4}$$

Where $\mathrm{m}_{\mathrm{it+x}}$ = the quote midpoint one minute after the trade where $\mathrm{x} = 1$

The price impact measures the adverse selection component in the effective spread (Riordan and Storkenmaier, 2012). It also implies gross losses of the liquidity suppliers to the liquidity demanders due to adverse selection. The price impact, $\mathrm{Pimpact}_{\mathrm{it}}$, is calculated with the quote midpoint one minute after the trade, meaning that x is equivalent to one in the equation (1.5) as follows:

$$\mathrm{Pimpact}_{\mathrm{it}} = \left[\mathrm{d}_{\mathrm{it}} \times \left(\frac{\mathrm{m}_{\mathrm{it+x}} - \mathrm{m}_{\mathrm{it}}}{\mathrm{m}_{\mathrm{it}}}\right)\right] \tag{1.5}$$

1.3.2 Measures of Intraday Price Discovery

This study investigates intraday price discovery using vector autoregression (VAR), impulse response functions (IRF), and cumulative impulse response functions (CIRF). The spread decomposition can represent the information contained in trades (Riordan and Storkenmaier, 2012). In the spirit of Hasbrouck (1991a, 1991b), Hendershott et al. (2011), Riordan and Storkenmaier (2012), Hirschey (2013), Chaboud, Chiquoine, Hjalmarsson, and Vega (2014), and Zhang (2018), VAR is exploited to investigate intraday price discovery in our study. Primarily, we follow the framework of Hasbrouck (1991a, 1991b), Hendershott et al. (2011), and Riordan and Storkenmaier (2012), who propose a VAR, IRF, and CIRF regarding the nature of information and trading by observing quotes and trades.[1]

The impact of trade on price due to information asymmetry can be measured (Hasbrouck, 1991a). Hasbrouck's model (1988, 1991a) proposed interaction between market makers and traders via quotes and trades in the stock exchange conditional on asymmetric

[1] Due to the unavailability of bid and ask price to calculate quote and trades, in this study we caluculate the bid and ask prices based on the availability of the data set provided by the SET, and trading regulations like price and time priority rules propsed by the SET.

information. He proposes that if the market makers are willing to buy or sell shares, they will post bid and ask quotes, which is revealed to traders. Trades happen after the prevailing quotes by market makers, and trading transactions will be characterised as positive when purchasing and negative when selling. In other words, the trade transaction indicates the direction of trades to be +1 when buying and -1 when selling. Suppose this model has no transaction cost and the announced trade only updates the public information set at time t. In that case, the revised quotes by market markers at the time are the summaries of the information that can be inferred from trades. News announcements are public information unrelated to trade, but private information concerns trade. The quote revision reflects private information, indicating the price impact of trades and that price moves due to private information. Therefore, the observed sequence of revised quotes and trades is inferred as trading and the nature of the information or order flow (Hendershott et al., 2011).

In the framework of Hasbrouck (1991a), we can classify price movements into price movements related to trades and unrelated to trade. We construct VAR with two equations. As shown in equation (1.6), the first equation is the change in quote revision in trade-by-trade. The model defines $r_{i,t}$ to be the log return of the quote midpoint of stock i from trade $t-1$ to trade t. As shown in equation (1.7), the second equation is the persistence of order flow and defines $y_{i,t}$ to be the purchase-sale indicator for trade at time t in stock i (+1 for purchase and -1 for sale). Both VAR models based on n lags of order flow are determined by Akaike Information Criteria (AIC), as shown in equations (1.6) and (1.7)

$$r_{i,t} = \sum_{j=1}^{n} \rho_j \, r_{i,t-j} + \sum_{j=0}^{n} \varphi_j \, y_{i,t-j} + \varepsilon_{i,r,t} \tag{1.6}$$

$$y_{i,t} = \sum_{j=1}^{n} \eta_j \, r_{i,t-j} + \sum_{j=1}^{n} \delta_j \, y_{i,t-j} + \varepsilon_{i,y,t} \tag{1.7}$$

Where $r_{i,t}$ = the log return of stock i at time t based on the quote midpoint changes of stock i from trade $t-1$ to trade t in a one-minute horizon,
$y_{i,t}$ = the trade direction of stock i at time t (+1 if buy and -1 if sell).

As shown in equations (1.6) and (1.7), Hasbrouck (1991a) explains that this VAR approach, which is applied to the quotes revision and trades, allows the resolution between public information (referred to the revised quotes innovation) and private information (referred to the trade innovation). As explained by Hasbrouck (1991a), the VAR approach is a Gaussian model robust to a dichotomic variable like trade direction or signed trade ($y_{i,t}$) because $\{y_{i,t}, r_{i,t}\}$ are jointly covariance stationary and invertible, making a VAR model given in equations (1.6) and (1.7) exist. The VAR model is also linear in signed trade of stock i at time t ($y_{i,t}$). Hasbrouck (1991a) also explains that the trades in this model are assumed to be exogenous and wholly unpredictable; the quote revisions will result in serial dependencies in trades, and the trades may be modelled similarly in equation (1.7). The disturbance in equation (1.17), $\varepsilon_{i,y,t}$, captures the unanticipated (innovative) trade component, so if there is any private information in trades, it has to reside in this innovation (Hasbrouck, 1991a).

Equations (1.6) and (1.7) will be estimated for each stock in the sample with a 1-minute horizon on each trading day. The VAR model in equations (1.6) and (1.7) express variables as a function of what occurred at time $t-1$ until time $t-n$ and the shocks of time t. However, what occurred at time $t-1$ depended on the shocks of time $t-1$ and on what occurred before time $t-1$. The vector moving average representation (VMA) clarifies how values at time t for the series are the cumulation of the effects of all the shocks from the past. The vector moving average representation (VMA) is the inversion of the VAR and can be defined as

$$z_{i,t} = \begin{bmatrix} r_{i,t} \\ y_{i,t} \end{bmatrix} = \psi(L)\varepsilon_{i,t} = \begin{bmatrix} a(L) & b(L) \\ d(L) & e(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{i,r,t} \\ \varepsilon_{i,y,t} \end{bmatrix} \tag{1.8}$$

Where $a(L), b(L), d(L),$ and $e(L)$ = polynomial lag operators,
$a(L)\varepsilon_{i,r,t} + b(L)\varepsilon_{i,y,t}$ = the permanent effect on price due to innovations (the quote revision innovation ($\varepsilon_{i,r,t}$) and the trade innovation ($\varepsilon_{i,y,t}$).

The Impulse Response Function (IRF) considers the response of the quoted price to a one-time unit shock in the order flow equation ($\varepsilon_{i,y,t}$). The Cumulative Impulse Response Function (CIRF) considers the cumulative response of the quoted price to a one-time unit shock in the order flow equation ($\varepsilon_{i,y,t}$). Thus, CIRF is a measure of asymmetric information (adverse selection) accounted for the continuation of order flow and the possibility of positive and negative trading (Hendershott et al., 2011). Following Hasbrouck (1991b), Hendershott et al. (2011), and Riordan and Storkenmaier (2012), the CIRF is found in the VMA representation and is equivalent to the sum of $\sum_{j=0}^{\infty} b_j$. The CIRF is the permanent price impact of trade and is interpreted as the private information residing in trade (Madhavan, 2000; Barclay and Hendershott, 2003; Riordan and Storkenmaier, 2012).

The covariance between the error term of equations (1.6) and (1.7) equals zero or $\mathrm{cov}(\varepsilon_{i,r,t}, \varepsilon_{i,y,t}) = 0$ because Hasbrouck (1991a) explained that the $r_{i,t}$ in equation (1.6) include the contemporaneous value of $y_{i,t}$ and the coefficients in equations (1.6) and (1.7) are linear projection coefficients, meaning that the quote revision and trades are not determined simultaneously. In other words, the quote revision, which is referred to as the log-returns of the quote midpoint changes, follows the trades and $r_{i,t}$ cannot contemporaneously effect $y_{i,t}$. The variance decomposition of random walk components is defined as

$$\sigma^2_{w_{i,t}} = \left(\sum_{j=0}^{\infty} a_j\right)^2 \sigma^2_{r_{i,t}} + \left(\sum_{j=0}^{\infty} b_j\right)^2 \sigma^2_{y_{i,t}} \tag{1.9}$$

In equation (1.9), the first term captures price changes relevant to trading, and the second term captures the price discovery component concerning recent trades (Hendershott et al., 2011).

Hasbrouck (1991a) also points out that in a market in which market participants exhibit differing capacities to obtain information, the information will be conveyed by trades and cause a permanent impact on stock prices. The effect of information in stock trades can be measured using the innovations (shocks) of stock trades from the price impact. Price changes stem from trade-related information components and trade-unrelated information components (or quote-related information components), and the vector autoregression (VAR) and the cumulative impulse response function (CIRF) can be exploited to analyse the private information that is conveyed by trades. The trade-related and quoted-related information represent the total amount of information in the stock market (Hasbrouck, 1991b). The unpredictable trade innovation is the crucial component that should be referred from the trades in terms of private information, not from the total trade (Hasbrouck, 1988), and the price impact of the trade innovation (shocks) may be defined as the impact of information on trades (Hasbrouck, 1991a).

1.3.3 The Effect of Market-wide and Stock-level Factors on Trade via Different Spread Measures

We test the hypothesis of whether a market-wide or stock-level factor significantly affects the trade via different spread measures: the price impact, the quoted spread, the effective spread, and the realised spread, as shown in the following equation:

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \sum_{\mathrm{k=1}}^{4} \beta_{\mathrm{k}} \mathrm{SET}_{\mathrm{i,d,k}} + \varepsilon_{\mathrm{i,d}} \tag{1.10}$$

Where $\mathrm{LM}_{\mathrm{i,d}}$ = The liquidity measures are the price impact, the quoted spread, the effective spread, and the realised spread, respectively, for stock i on day d,

α = A fixed cross-sectional effect for all stock in our sample.

$\mathrm{SET}_{\mathrm{i,d,k}}$ = Three market-wide factors for stock i on day d, namely the realised volatility, the SET index's returns, and the market capitalisation of the SET and one stock-level factor for stock i on day d, which is the turnover ratio of stocks.

To avoid noise in high-frequency data, we aggregate observations in the one-minute horizon to a daily frequency for analysis using regression analysis with panel data (Riordan and Storkenmaier, 2012). For robustness, we follow Riordan and Storkenmaier (2012), who aggregate the observations in the five-minute horizon into a daily observation. However, the results we obtain from observations used in the five-minute and one-minute horizons are similar, so we represent only results from observations used in a one-minute horizon.

We will use a panel data regression analysis that controls for random effects and includes three daily market-wide factors (realised volatility, the returns of the SET index, and the natural logarithm of the market capitalisation of the SET) and one daily stock-level factor (turnover ratio of stocks) that affect trade via different spread measures. The realised volatility, turnover ratio of stocks, the SET index's natural logarithm, and the SET's market capitalisation are calculated as follows.

The realised volatility (RV_{d}) of the SET index is calculated as the sum of squared returns in the following equation (Li and Yao, 2021; Lin et al., 2022).

$$\mathrm{RV}_{\mathrm{d}} = \sum_{\mathrm{d=1}}^{30} \mathrm{r}_{\mathrm{d}}^{2} \tag{1.11}$$

Where r_{d} = the returns of the SET index on day d

Turnover ratio or volume turnover refers to the daily trading turnover ratio of stocks. It aims to measure the daily volume of security trading relative to the current volume of the listed shares calculated as a percentage (SETSMART, 2023a), as shown in the following equation.

$$\mathrm{TR}_{\mathrm{id}} = \frac{\mathrm{Vol}_{\mathrm{id}}}{\mathrm{Share}_{\mathrm{id}}} \times 100 \tag{1.12}$$

Where $\mathrm{TR}_{\mathrm{id}}$ = daily turnover ratio in stock i

$\mathrm{Vol}_{\mathrm{id}}$ = daily trading volume in traded stock i

$\mathrm{Share}_{\mathrm{id}}$ = number of listed shares i which is traded on that day

The SET index is a composite index and a market capitalization-weighted price index calculated from the prices of all common stocks on the main board in the SET (SET, 2023c). The SET index also represents the price movement for all common stock trading on the SET (SET, 2023c). This is the most typical index that financial participants use to monitor the price movement of stocks traded in the SET. The SET index is calculated as follows:

$$\text{SET index} = \frac{\text{Current Market Value}}{\text{Base Market Value}} \times 100 \tag{1.13}$$

Therefore, the returns of the SET (ret) is calculated as follows:

$$ret = ln(SET_d) - ln(SET_{d-1}) \tag{1.14}$$

Where SET_d = the closing price of the SET index on day d

SET_{d-1} = the closing price of the SET index on day d-1

Current market value refers to the market capitalisation value on that day. The base market value in calculating the SET index is 30th April 1975 (SET, 2023c), and the base value is 100 points. Market capitalization (MCap) refers to the overall market value of listed securities on that day in the SET calculated from the daily closing price of listed securities multiplied by the current number of listed shares in the SET on the same day (SETSMART, 2023b).

$$\text{MCap} = \text{Closing price of shares} \times \text{number of listed shares} \tag{1.15}$$

We also conducted this panel regression analysis by transforming equation (1.10) into twelve models for analysis: four univariate analyses, five bivariate analyses, and three multivariate analyses, as follows.

Firstly, we conducted a panel regression analysis with four univariate analyses, as shown in model (1)-(4) in equations (1.16)-(1.19).

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{rv}\mathrm{SET}_{\mathrm{i,d,rv}} + \varepsilon_{\mathrm{i,d}} \tag{1.16}$$

Where $SET_{i,d,rv}$ = the realised volatility of the SET index on stock i on day d,
$\mathrm{LM}_{\mathrm{i,d}}$ = the liquidity measures comprised of the price impact, the quoted spread, the effective spread, and the realised spread, respectively, for stock i on day d.

In model (1) or equation (1.16), we conduct four different dependent variables with the same independent variable, and this fashion will be applied to the following eleven models.

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{tr}\mathrm{SET}_{\mathrm{i,d,tr}} + \varepsilon_{\mathrm{i,d}} \tag{1.17}$$

Where $SET_{i,d,tr}$ = turnover ratio of stocks i on day d.

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{ret}\mathrm{SET}_{\mathrm{i,d,ret}} + \varepsilon_{\mathrm{i,d}} \tag{1.18}$$

Where $SET_{i,d,ret}$ = the returns of the SET index on stock i on day d.

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{mcap}\mathrm{SET}_{\mathrm{i,d,mcap}} + \varepsilon_{\mathrm{i,d}} \tag{1.19}$$

Where $SET_{i,d,mcap}$= the natural logarithm of the market capitalisation on stock i on day d.

Secondly, we conducted a panel regression analysis with five bivariate analyses, as shown in models (5)-(9) in equations (1.20)-(1.24), respectively.

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{rv}\mathrm{SET}_{\mathrm{i,d,rv}} + \beta_{tr}\mathrm{SET}_{\mathrm{i,d,tr}} + \varepsilon_{\mathrm{i,d}} \tag{1.20}$$

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{rv}\mathrm{SET}_{\mathrm{i,d,rv}} + \beta_{ret}\mathrm{SET}_{\mathrm{i,d,ret}} + \varepsilon_{\mathrm{i,d}} \tag{1.21}$$

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{rv}\mathrm{SET}_{\mathrm{i,d,rv}} + \beta_{mcap}\mathrm{SET}_{\mathrm{i,d,mcap}} + \varepsilon_{\mathrm{i,d}} \tag{1.22}$$

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{tr}\mathrm{SET}_{\mathrm{i,d,tr}} + \beta_{ret}\mathrm{SET}_{\mathrm{i,d,ret}} + \varepsilon_{\mathrm{i,d}} \tag{1.23}$$

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{tr}\mathrm{SET}_{\mathrm{i,d,tr}} + \beta_{mcap}\mathrm{SET}_{\mathrm{i,d,mcap}} + \varepsilon_{\mathrm{i,d}} \tag{1.24}$$

Lastly, we conducted a panel regression analysis with three multivariate analyses, as shown in models (10)-(12) in equations (1.25)-(1.27), respectively.

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{rv}\mathrm{SET}_{\mathrm{i,d,rv}} + \beta_{tr}\mathrm{SET}_{\mathrm{i,d,tr}} + \beta_{ret}\mathrm{SET}_{\mathrm{i,d,ret}} + \varepsilon_{\mathrm{i,d}} \tag{1.25}$$

$$\mathrm{LM}_{\mathrm{i,d}} = \alpha + \beta_{rv}\mathrm{SET}_{\mathrm{i,d,rv}} + \beta_{tr}\mathrm{SET}_{\mathrm{i,d,tr}} + \beta_{mcap}\mathrm{SET}_{\mathrm{i,d,mcap}} + \varepsilon_{\mathrm{i,d}} \tag{1.26}$$

$$\begin{aligned}\mathrm{LM}_{\mathrm{i,d}} = \alpha &+ \beta_{rv}\mathrm{SET}_{\mathrm{i,d,rv}} + \beta_{tr}\mathrm{SET}_{\mathrm{i,d,tr}} + \beta_{ret}\mathrm{SET}_{\mathrm{i,d,ret}} \\ &+ \beta_{mcap}\mathrm{SET}_{\mathrm{i,d,mcap}} + \varepsilon_{\mathrm{i,d}}\end{aligned} \tag{1.27}$$

As seen in all twelve models from above equations (1.16)-(1.27), the most important model that we focus on is model twelve in equation (1.27) to investigate the simultaneous influence of market-wide and stock-level factors on the spread measures, primarily focus on the price impact of trades.

1.4 The Data Collection

In studying intraday liquidity, price discovery, and price impact, we collected trading data from the SET (Stock Exchange of Thailand) for six months between January 2019 and June 2019. Regarding this trading data, we can identify every order with the tick-by-tick time stamp, the company code, the type of investors, the stock price, the volume of each trade, and the trade direction (buy or sell). This trading data also spans 10:05 AM - 12:25 PM and 2:35 PM - 4:25 PM local time each day, because there are separate trading sessions in the morning and afternoon.

The sample observations incorporate the 98 stocks that comprise the SET100 Index. The SET100 is a combination of 2 groups of stocks. The first group consists of stocks in the SET50 index, the 50 largest and highest quality Thai blue-chip stocks determined by market capitalisation, free-float, transparency regulations, and industries. The second group is comprised of another 50 second-largest and second-highest quality Thai stocks. The SET 100 Index is the most 100 actively traded stocks and the highest quality publicly traded Thai companies and presents a broad cross-section of industries. However, stocks in the SET100

Index that are split or delisted during the observation period are removed. The results of the intraday liquidity, intraday price discovery and the effect of market-wide factors on trade are reported for the entire sample and four different MCap quartiles.

1.5 Results

1.5.1 Descriptive Statistics

Table 1.1 reports the market capitalisation, price, quoted spread, effective spread, realised spread, and price impact for all stocks in the sample of 98 stocks listed in SET's SET100 Index between January and June 2019.

The 10-year average market capitalisation of sample stocks is 106,267 Thai Baht. There is a vast range between the maximum and minimum market capitalisation of sample stocks with a difference of 1,008,58 million THB (Thai Baht). The quoted spread is approximately 32.25 bps throughout the sample period, ranging from a minute average of 12.52 bps to 513.83 bps. The value of the effective spread is less than that of the quoted spread, which is consistent with the results of Riordan and Storkenmaier (2012), who find that the effective spread is less than the quoted spread. This ranges from a minimum of 12.52 to a maximum of 185.19. Suppose the quoted spread is greater than the effective spread. This would imply that all market participants in the SET actively monitor the market in search of satisfactory liquidity conditions (Riordan and Storkenmaier, 2012). Such instances will lead to price improvement or a situation in which the executed price is between the bid price and the ask price of the quoted spread, as market makers or dealers act in quote-driven stock markets. Simultaneously, the higher value of the quoted spread compared to the effective spread in this study indicates that all market participants in the SET actively look for favourable liquidity. Besides, the effective spread, which is the cost paid by the liquidity demander, comprises two essential components: realised spread, which is the revenue of the liquidity providers (or suppliers), and price impact, which is the cost of adverse selection or asymmetric information. In Table 1.1, the realised spread is 28.57 bps, the price impact is 1.76 bps, and the value of the realised spread is more than tenfold (16.23 times) higher than the value of the price impact. Finally, there are 1,406,903 observations in this study.

Table 1.1: Market Summary Statistics

Variable	Unit	Mean	Min	Max	Std	Skewness	Kurtosis
Market Cap	Million THB	106,267	1,064	1,009,652	154,688	3.05	14.62
Price	THB	47.12	0.52	490.00	70.20	3.55	18.70
Quoted Spread	basis points (bps)	32.25	12.52	513.83	15.43	2.89	23.72
Effective Spread	basis points (bps)	30.34	12.52	185.19	11.67	1.16	5.87
Realised Spread	basis points (bps)	28.57	-245.61	285.71	18.11	-0.67	13.10
Price Impact	basis points (bps)	1.76	-253.97	280.70	14.16	2.78	34.35
Number of observations							1,406,903

Tables 1.2 and 1.3 provide information in relation to the summation of trade volume and trade value, categorised by three groups of market participants: individual investors (or local investors or retail investors), foreign investors, and institutional investors, spanning a period of six months (January – June 2019), and also reports in groups of stocks in 4 quartiles of market capitalisation.

Individual investors are the most influential market participants, with the highest trade volume. This result is in line with the findings of Pavabutr and Prangwattananon (2009) and OECD (2023), which confirms that the Stock Exchange of Thailand is dominated by local investors (or retail/individual investors). A similar trend also happens, with 54.55 and 69.33 per cent, in MCap quartiles 2 and 1.

In contrast, the market participants who play a crucial role by submitting the most considerable trade value in the market are foreign investors, with 42.88 per cent (56.12 Billion THB) of total trade value, compared to those of the remaining two market participants: individual investors and institutional investors, with 36.82 (48.18 Billion THB) and 20.30 per cent (26.57 Billion THB) respectively. Likewise, in MCap quartiles 4 and 3, this trend is still the same. However, in MCap quartiles 2 and 1, the individual investors are the critical group with the most significant trade value, with 49.70 and 61.75 per cent in MCap quartiles 2 and 1, respectively, meaning that the individual investors are more likely to trade in lower value stock. Interestingly, all three groups of market participants trade the most in MCap quartile 4, compared to their trade value in the remaining three quartiles of market capitalisation.

Table 1.2: Market Summary Statistics in Trading Volume

Stocks	Individual Investors[2]		Foreign Investors		Institutional Investors[3]	
	Order Volume (Million stocks)	%	Order Volume (Million stocks)	%	Order Volume (Million stocks)	%
Overall	3,647.27	51.03	2,365.78	33.10	1,134.43	15.87
4Q MCap	531.41	34.39	706.39	45.72	307.24	19.89
3Q MCap	735.89	41.39	741.37	41.70	300.77	16.92
2Q MCap	1,001.83	54.55	512.64	27.91	322.02	17.53
1Q MCap	1,378.15	69.33	405.38	20.39	204.40	10.28

Notes: This market summary statistics in trading volume reports in overall and in market participant types: individual, foreign, and institutional.

[2] Individual investors are equivalent to local individuals, which is categorized as type of market participants by the SET.

[3] Institutional investors are equivalent to local institutions, which is categorized as type of market participants by the SET.

Table 1.3: Market Summary Statistics in Trading Value

Stocks	Individual Investors		Foreign Investors		Institutional Investors	
	Order Value (Billion THB)	%	Order Value (Billion THB)	%	Order Value (Billion THB)	%
Overall	48.18	36.82	56.12	42.88	26.57	20.30
4Q MCap	21.68	29.87	35.39	48.75	15.52	21.38
3Q MCap	9.93	35.71	12.25	44.07	5.62	20.23
2Q MCap	9.24	49.70	5.73	30.82	3.62	19.48
1Q MCap	7.33	61.75	2.74	23.06	1.80	15.19

Notes: This market summary statistics in trading value report in overall and in market participant types: individual, foreign, and institutional.

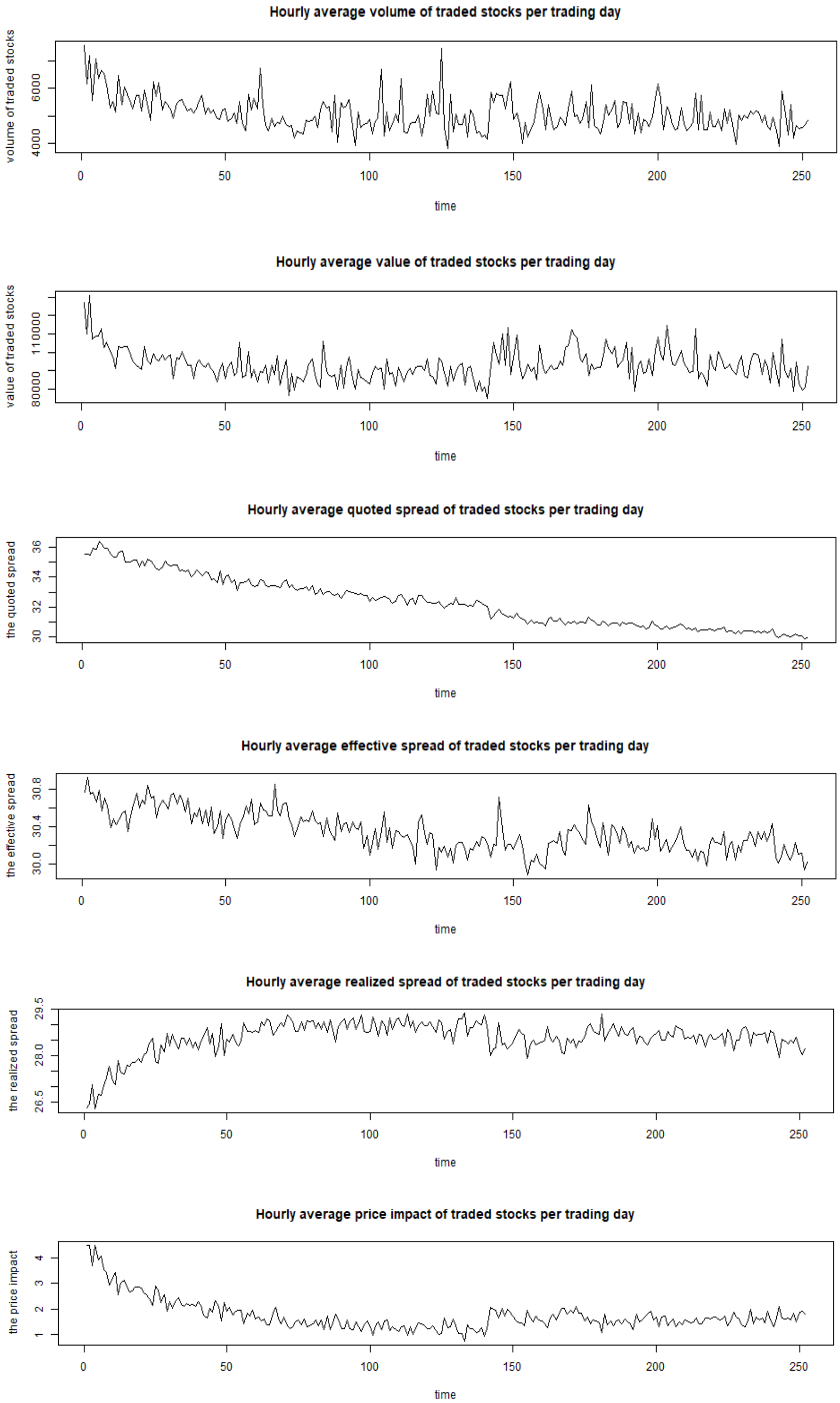
Figure 1.1 illustrates the hourly average trading volume, trading value, quoted spread, effective spread, realised spread, and the price impact of all market participants per trading day span throughout the first six months of 2019. The trading volume and value follow the U-shaped pattern, indicating higher trading transactions at the market open, decline massively during the trading session in the middle of the trading day and then return to the higher trading transaction again at the closing market, similar to the market's opening. These findings are consistent with the findings of Brock and Kleidon (1992). They explain that in the quote-driven market, the demand for transactions at the opening and closing of the trading day in the market is higher than in the middle of the trading day. The demand for holding optimal positions in the high demand for trading transactions generates an intraday seasonal effect. In order-driven markets, Chung et al. (1999) propose that the competition among the limit orders causes the intraday seasonal effect, reflecting the U-shaped pattern. The quoted spread represents an inverted J-shaped pattern, meaning that the intraday pattern of the quoted spread shows the pattern that is high on the opening trading day, declines during the trading day after the market opens and narrows down approaching the market close (Chan et al., 1995), consistent with the results of Ozturk et al. (2017). Admati and Pfleiderer (1998) explain that the intraday seasonality effect follows an inverted J-shaped pattern due to the presence of asymmetric information at the market open between the noise traders and the informed traders, leading to a broader quote spread and increased volatility.

There are two trading sessions in the SET: the morning trading session, as shown in the first half of the figure on the left-hand side, and the afternoon trading session, as illustrated in the second half of the figure on the right-hand side. The SET sees the highest trade volume and the highest trade value at the beginning of the morning session, but, on average, the SET sees a higher trade value in the afternoon trading session than in the morning trading session. By contrast, the widest quoted spread occurs at the beginning of the morning trading session, and it gradually declines until the narrowest quoted spread is found at the end of the afternoon trading session. Likewise, the value of the effective spread begins with the highest value at the beginning of the morning trading session, stays at the high level until the middle of the morning trading session, and then has a fluctuated decline until the end of the afternoon trading session, meaning that the liquidity demanders who would like to execute immediately have the highest trading cost in the first half of the morning trading session.

The value of the realised spread starts at the lowest value at the beginning of the morning trading session, stays at the highest value in the middle of the morning trading session and remains at that level until the end of the morning trading session, then slightly drops during the afternoon trading session, meaning that the liquidity providers who place their orders in the limit order book will obtain the lowest revenues at the beginning of the morning trading session in every trading day.

Simultaneously, the price impact starts with the highest value at the beginning of the morning trading session, rapidly drops to the lowest value at the end of the morning trading session, and then slightly increases during the afternoon trading session until the end. These findings imply that the market participants, who are the liquidity providers, or who submit their orders in the limit order book, will experience the most impact of adverse selection (or asymmetric information), or will have tremendous gross losses to the liquidity demanders at the beginning of the morning trading session. However, this highest impact of asymmetric information will rapidly decline and reach the lowest point at the end of the morning trading session, and then slightly increase in the afternoon session until the close of trading.

Figure 1.1: Hourly Intraday Averages of Trading Volume, Trading Value, and the Different Spread Measures



Notes: This figure reports the hourly intraday average of trading volume, trading value, and the different spread measures, which are the quoted spread, the effective spread, the realised spread, and the price impact, respectively. This figure also reports the data spanning from January to June 2019.

1.5.2 Main Results

1.5.2.1 Measurement of Intraday Liquidity: Analysis of Different Spread Measures

Table 1.4 reports the descriptive statistics of liquidity and different spread measures. The means, min, max, standard deviation, skewness and kurtosis are represented for the entire observation period, and they are also shown for both four market capitalisation quartiles (MCap).[4]

The quoted spread equals 32.25 bps with a range between the minimum value of 12.52 bps and the maximum of 518.83 bps. The effective spread is smaller than the quoted spread, at approximately 30.34 bps throughout the sample period. It ranges from a minute average of between 12.52 bps and 185.19 bps. The higher value of the quoted spread when compared to the effective spread in this study is consistent with the findings of Riordan and Storkenmaier (2012) that the quoted spread is greater than the effective spread. They conclude that the stock market participants or investors actively monitor the market for satisfied liquidity conditions. Likewise, these findings suggest that the SET market participants who submit the limit orders continuously monitor the market and will likely obtain an informational advantage as the SET changes its condition. In such instances, the market participants will be less likely to incur the problem of the stale price and the stale limit orders along with the higher probability of execution or lower risk of nonexecution, meaning that they probably avoid the picking-off risk through future informed trading.[5] by future informed trading. This active monitoring of market participants in the SET also leads to the decreased risk of the waiting cost for execution.

In addition, the quoted spread and effective spread increase across the lower MCap quartiles from 26.48 bps and 24.84 bps in MCap quartile 4 to 38.49 bps and 35.87 bps in MCap quartile 1. The direction of the quoted spread value suggests that the SET market participants tend to undergo a higher transaction cost when trading stocks with lower market capitalisation. In the meantime, in the case of the effective spread, the liquidity demanders seem to pay more spread in trading the lower market-cap stocks in the SET.

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[4] MCap quartile 4 is the group of stocks with the largest market capitalisation, and MCap quartile 1 is the group of stocks with the fourth-largest market capitalisation. The components of stocks in each quartile are shown in Table A.2 of the appendix.

[5] The risk occurs when there is a stale limit order that is not modified or cancelled in time while orders from incoming informed investors arrive.

The realised spread and the price impact also increase across the lower MCap quartiles, as the quoted and effective spread do. These findings indicate that, in the case of the realised spread, the revenue of the liquidity suppliers seems to increase as they trade stock with a lower market capitalisation. In the meantime, in terms of the price impact, there is an increase in trade information, causing the liquidity suppliers to be less able to handle adverse selection or information asymmetry simultaneously.

It is worth noting that the MCap quartiles 4 and 1 have the lowest and highest values of the quoted spread, effective spread, realised spread, and price impact. The answer from Rosu (2020) may help explain this result. His findings explain the interplay between the bid-ask spread and the informed share.[6] The equilibrium bid-ask spread is a negative function of the informed share. As such, this would imply that MCap quartile 4 is distinguished by the largest proportion of informed traders and more competition between informed traders in trading stocks in comparison with their lower market capitalisation counterparts.

Conversely, it is likely to imply that the smallest proportion of informed traders and lowest level of competition between informed stock traders occurs in MCap quartile 1 compared to other quartiles. Regarding the price impact, Hasbrouck (1991a) underscores that asymmetric information or adverse selection significantly occurs in stocks with smaller market capitalisation, like MCap quartile 1. Healy and Palepu (2001) also comment that companies may reduce information asymmetry with good corporate disclosure practices of substantial market capitalisation. Hence, companies in MCap quartile 4 have the lowest price impact in the SET.

To sum up, we can conclude that stocks in the SET100 Index show diminished levels in comparison with smaller-capitalisation counterparts listed outside the SET100 Index in terms of asymmetric information, transaction costs, and price impact, consistent with Hasbrouck's (1991a, 1991b) findings. There are changes in all spread measures across all MCap quartiles, but their values slightly change. Our results typically exhibit lower information asymmetry and enhanced liquidity as market capitalisation increases across Mcap quartiles from 1 to 4. These findings are also supported by the findings of Healy and Palepu (2001),

[6] Rosu (2020) defines the concise word of the proportion of informed traders who trade with superior information, namely the informed share. In limit order markets, his dynamic model suggests that a larger fraction of informed traders improves liquidity without the price impact of trades. Such instances arise depending upon two key features of his model: there is competition among informed traders, and private information is long-lived. Consequently, the larger proportion of informed traders can eventually overcome the static increase in adverse selection.

Diamond and Verrechia (1991), and Boone and White (2015), all of whom argue that the better corporate disclosure practices of larger market capitalisation firms help reduce information asymmetry because (i) they can attract larger investors like institutional investors and (ii) the institutions require more transparency on larger-cap companies with higher institutional ownership, resulting in increased liquidity and decreased price impact of trades in their stocks.

Table 1.4: Descriptive Statistics in Liquidity and Different Spread Measures

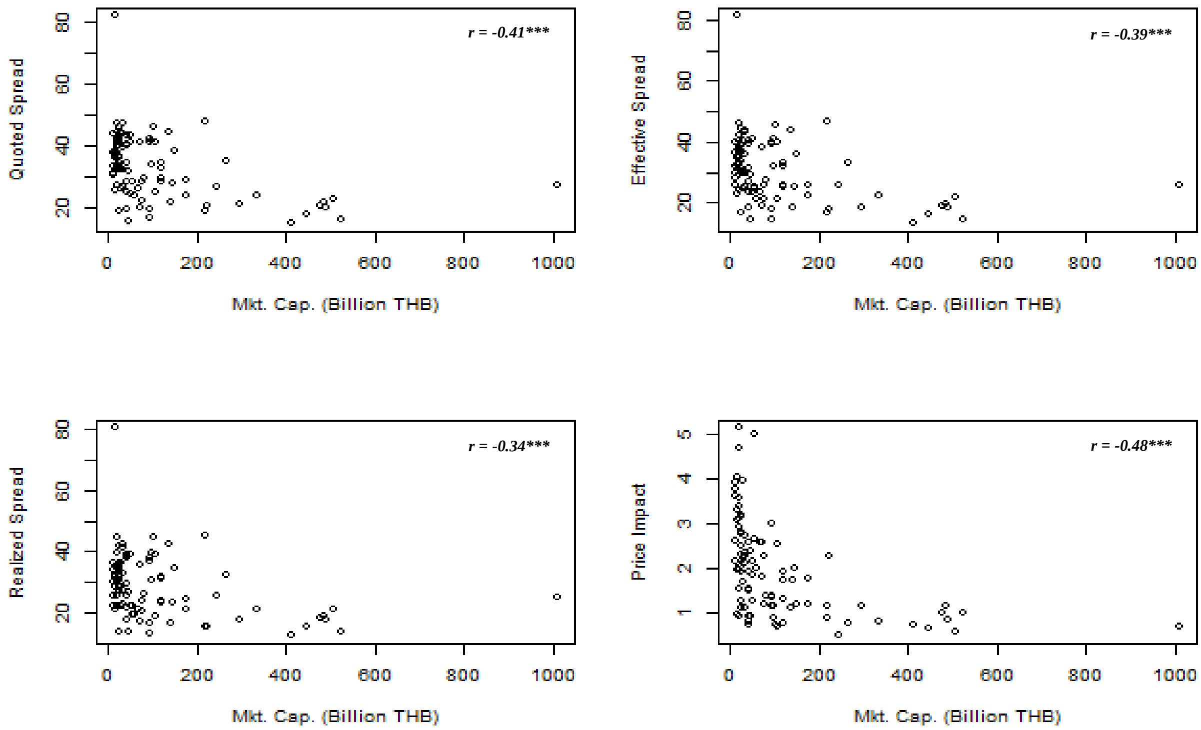
	No. of Stocks	No. of Observations	Quoted Spread						Effective Spread					
			Mean	Min	Max	Std.	Skewness	Kurtosis	Mean	Min	Max	Std.	Skewness	Kurtosis
All Stocks	98	1,406,903	32.25	12.52	513.83	15.43	2.89	23.72	30.34	12.52	185.19	11.67	1.16	5.87
Quartile														
4Q MCap	24	457,048	26.48	12.52	289.02	12.91	2.61	18.35	24.84	12.52	98.04	10.14	1.36	3.97
3Q MCap	25	352,360	31.79	12.90	236.22	13.85	2.08	14.07	30.24	12.90	99.01	10.87	0.46	2.41
2Q MCap	25	323,375	35.60	12.52	513.83	15.18	3.78	39.12	33.50	12.52	142.18	9.98	0.45	4.36
1Q MCap	25	274,120	38.49	20.04	353.70	17.84	3.34	23.05	35.87	20.04	185.19	12.87	2.28	9.53
	No. of Stocks	No. of Observations	Realised Spread						Price Impact					
			Mean	Min	Max	Std.	Skewness	Kurtosis	Mean	Min	Max	Std.	Skewness	Kurtosis
All Stocks	98	1,406,903	28.57	-245.61	285.71	18.11	-0.67	13.10	1.76	-253.97	280.70	14.16	2.78	34.35
Quartile														
4Q MCap	24	457,048	23.72	-125.94	175.44	14.59	-0.16	10.81	1.12	-150.38	151.13	10.56	2.47	35.88
3Q MCap	25	352,360	28.63	-215.95	204.08	17.19	-0.97	12.60	1.61	-178.17	249.17	13.43	2.70	33.16
2Q MCap	25	323,375	31.52	-203.56	246.58	17.96	-1.32	15.10	1.98	-219.18	242.91	15.21	2.78	29.90
1Q MCap	25	274,120	33.11	-245.61	285.71	22.32	-0.82	13.19	2.76	-253.97	280.70	18.37	2.43	26.56

Notes: This descriptive statistic reports in the sample observations incorporating the 98 stocks and in 4 quartiles of market capitalisation (in a 1-minute horizon)[7]

[7] We also perform a similar calculation with a 5-minute interval, and there is no significantly qualitative difference in our findings.

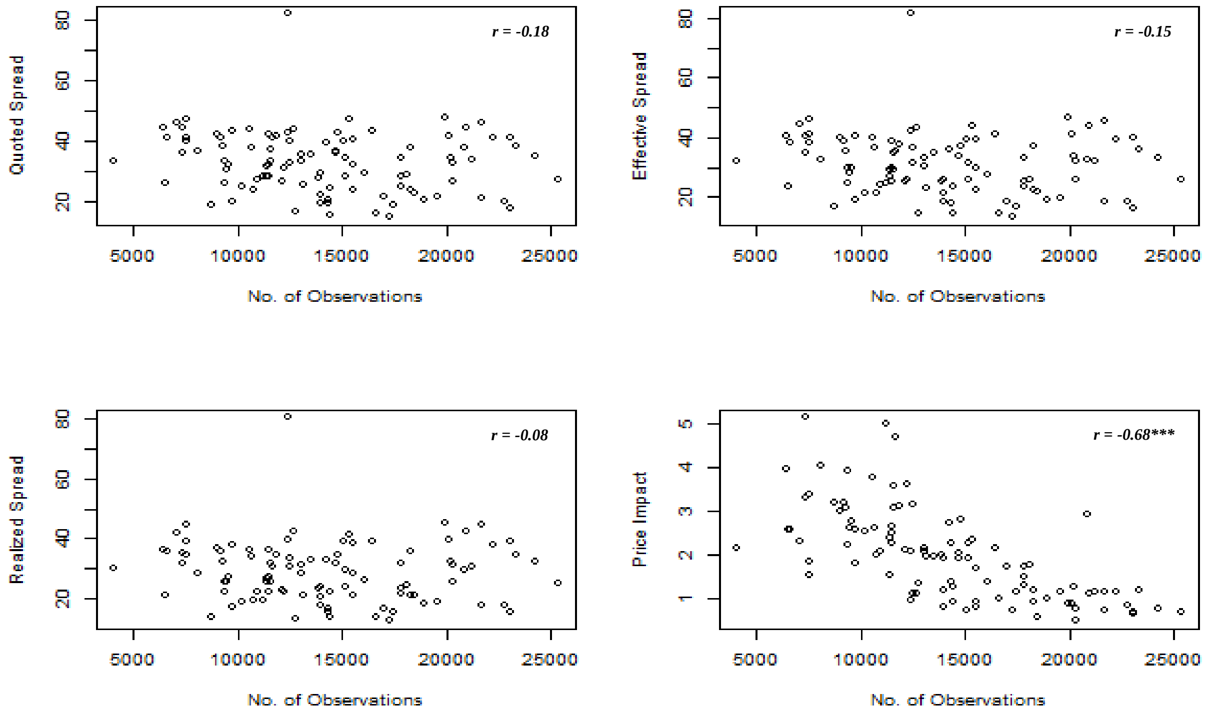
Figure 1.2 illustrates the relationship between different spread measures (the quoted spread, the effective spread, the realised spread, and the price impact) and the market capitalisation of each stock in our sample. There are negative relationships between different spread measures and market capitalisation, consistent with our findings in Table 1.4. Figure 1.3 depicts the relationship between the different spread measures and the number of observations of each stock in our sample. The interesting subject is the relationship between the price impact and the number of observations, which is indirectly inherent in how liquid the traded stocks are. Moreover, the increasing number of observations implies that there are more active traded stocks. With the strong and statistically significant correlation at a 1% significant level, the more liquid the stock is, the less price impact (adverse selection or information asymmetry) there will be. This result is in line with the findings of Easley et al. (1996) and Lim and Coggins (2005), which confirm that less liquid stocks incur more price impact than more liquid stocks. This finding is also consistent with Kraus and Stoll (1972), Loeb (1983), Holthausen et al. (1987), and Keim and Madhavan (1996), who study the price impact of block trades in stock markets such as the New York Stock Exchange (NYSE). Moreover, stocks with larger capitalisation are inherently more liquid and have a more active value of trades (Lim and Coggins, 2005).

Figure 1.2: Scatter Plots Illustrating the Relationship Between Market Capitalisation and the Different Spread Measures



Notes: This figure reports scatter plots illustrating the relationship between market capitalisation and the different spread measures, which are the quoted spread, the effective spread, the realised spread, and the price impact, respectively. This figure is also reported using the sample observations incorporating the 98 stocks comprising the SET100 index in a 1-minute horizon.

Figure 1.3: Scatter Plots Illustrating the Relationship Between the Number of Observations and the Different Spread Measures

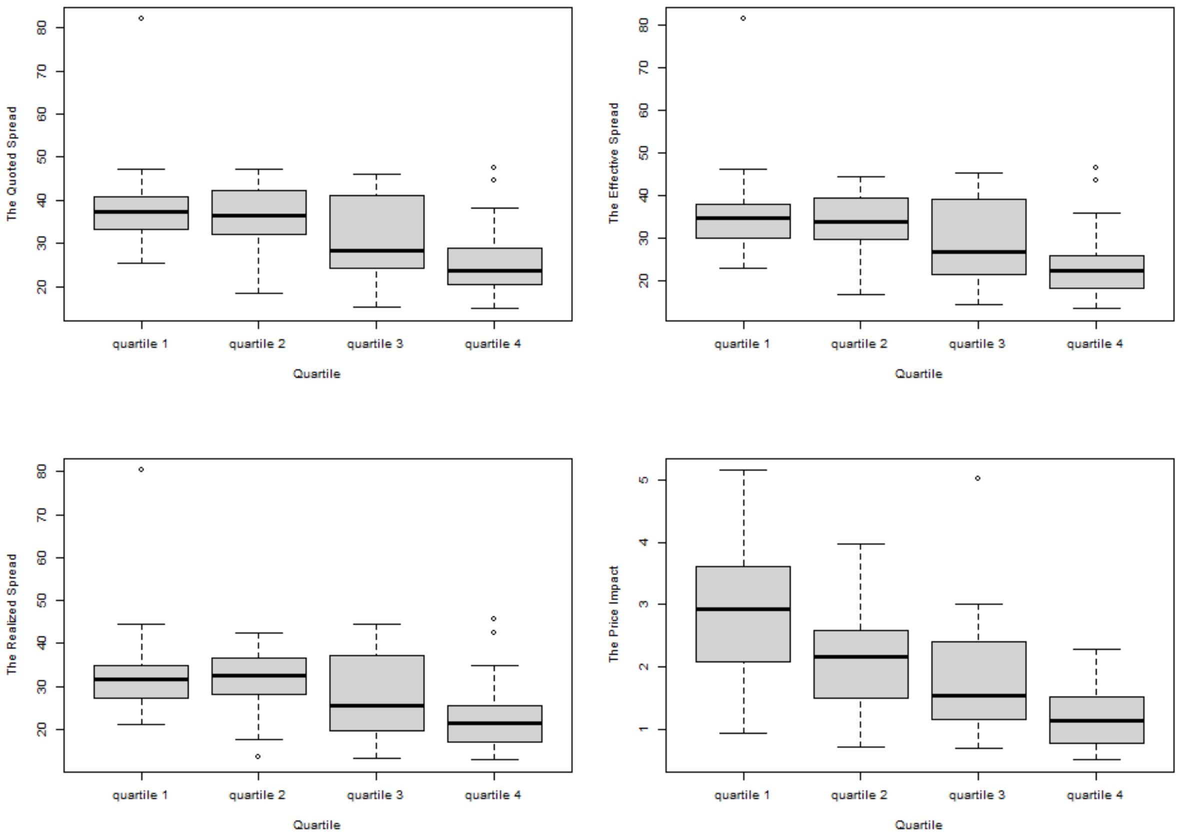


Notes: This figure reports the scatter plots illustrating the relationship between the number of observations and the different spread measures, which are the quoted spread, the effective spread, the realised spread, and the price impact, respectively. This figure is also reported using the sample observations incorporating the 98 stocks comprising the SET100 index in a 1-minute horizon.

Figure 1.4 represents four diagrams of boxplots displaying the distribution of the values of different spread measures (the quoted spread, the effective spread, the realised spread, and the price impact) of stocks in four quartiles and making a comparison between values of different spread measures of 98 stocks with different market capitalisation, categorised into four quartiles. In general, the boxplot represents the distribution of the dataset based upon a five-number summary: the minimum value (or the lowest data point excluding outliers: Q1-1.5*IQR), the first quartile (Q1 or 25th percentile), the median (or the middle value of the dataset), the third quartile (Q3 or 75th percentile) and the maximum value (or the highest data point excluding outliers: Q3+1.5*IQR). Also, the boxplot can detect outliers lower than the minimum value or greater than the maximum value and gives information regarding most of the dataset via the interquartile range (IQR: Q3-Q1 or 25th to 75th percentile).

In the two upper diagrams we can see that the median values of the quoted spread and the effective spread across four different MCap quartiles exhibit nearly identical patterns. This aspect arises because around three-quarters of our observations are marketable orders. The median values of the effective spread and the realised spread across four different MCap quartiles differ. So, we can conclude that the four quartiles have different median values of spread measures. They are negatively correlated with the level of the MCap quartile. These findings indicate negative relationships between different spread measures and market capitalisation, consistent with our findings in Table 1.4 and Figure 1.2.

Figure 1.4: Boxplots Illustrating the Median Values and the Spread of the Values of the Different Spread Measures



Notes: This figure reports the boxplots illustrating the median values and the spread of the values of the different spread measures, which are the quoted spread, the effective spread, the realised spread, and the price impact, respectively. This figure is also reported using the sample observations incorporating the 98 stocks comprising the SET100 index with different market capitalisations categorised into four quartiles in a 1-minute horizon.

Table 1.5 reports the Welch one-way test (one-way ANOVA test, relaxing the homogeneity of variance assumption). The results confirm significant differences between means of the different spread measures (the quoted spread, the effective spread, the realised spread, and the price impact) across four MCap quartiles. We then conduct pairwise comparisons using a t-test that relaxes the homogeneity of variance assumption. Evidence shows that the mean values of the quoted spread, the effective spread, and the realised spread in MCap quartile 4 significantly differ from MCap quartiles 2 and 1. The mean value of the quoted spread, the effective spread, and the price impact in MCap quartile 3 also differs statistically from those in MCap quartile 1. The mean value of the price impact in MCap quartile 2 also differs statistically from those in MCap quartile 1. Therefore, the findings from Figures 1.2, 1.3 and 1.4 and Table 1.5 help confirm the findings found in Table 1.4 that the different spread measures inversely change across the MCap quartiles.

Table 1.5: ANOVA Test for Spread Measures of Four Different MCap Quartiles

Variables	Quartile 4 (Mean)	Quartile 3 (Mean)	Quartile 2 (Mean)	Quartile 1 (Mean)	ANOVA (p-value)	Statistically significant difference between four quartiles
Quoted Spread (QS)	26.14	30.75	35.84	38.40	1.02×10^{-4}	Yes
Effective Spread (ES)	24.45	29.08	33.70	35.86	3.14×10^{-4}	Yes
Realised Spread (RS)	23.28	27.26	31.60	33.00	2.03×10^{-3}	Yes
Price Impact (PI)	1.17	1.82	2.11	2.86	6.91×10^{-9}	Yes
No. of Stocks	24	25	25	25		
Observations	457,048	352,360	323,375	274,120		1,406,903
Pairwise Comparison					t-test (p-value)	Statistically significant difference between two quartiles
Quoted Spread (QS)						
Quartiles 4 and 3					0.0916	No
Quartiles 4 and 2					5.20×10^{-4}	Yes
Quartiles 4 and 1					3.00×10^{-4}	Yes
Quartiles 3 and 2					0.0642	No
Quartiles 3 and 1					0.0175	Yes
Quartiles 2 and 1					0.3390	No
Effective Spread (QS)						
Quartiles 4 and 3					0.0932	No
Quartiles 4 and 2					7.40×10^{-4}	Yes
Quartiles 4 and 1					7.40×10^{-4}	Yes
Quartiles 3 and 2					0.0906	No
Quartiles 3 and 1					0.0451	Yes
Quartiles 2 and 1					0.4223	No
Realised Spread (RS)						
Quartiles 4 and 3					0.1576	No
Quartiles 4 and 2					4.50×10^{-3}	Yes
Quartiles 4 and 1					4.50×10^{-3}	Yes
Quartiles 3 and 2					0.1192	No
Quartiles 3 and 1					0.1161	No
Quartiles 2 and 1					0.6089	No
Price Impact (PI)						
Quartiles 4 and 3					7.70×10^{-3}	Yes
Quartiles 4 and 2					7.20×10^{-5}	Yes
Quartiles 4 and 1					1.40×10^{-7}	Yes
Quartiles 3 and 2					0.2629	No
Quartiles 3 and 1					1.30×10^{-3}	Yes
Quartiles 2 and 1					8.80×10^{-3}	Yes

1.5.2.2 Measurement of Intraday Price Discovery: Analysis of Impulse Response Function (IRF) and Cumulative Impulse Response Function (CIRF)

This study uses 98 stocks with 1-minute and 5-minute intervals in the sample to measure intraday price discovery. It applies information criteria determine the lag length for each stock in a more suitable model based on the value of Akaike Information Criteria (AIC). In vector autoregression (VAR) models of each stock, the results suggest that the system is stable because each model has almost identical values of characteristic roots. Also, there are similar results between a 1-minute and 5-minute interval, so the study will only provide the results of a 1-minute horizon.

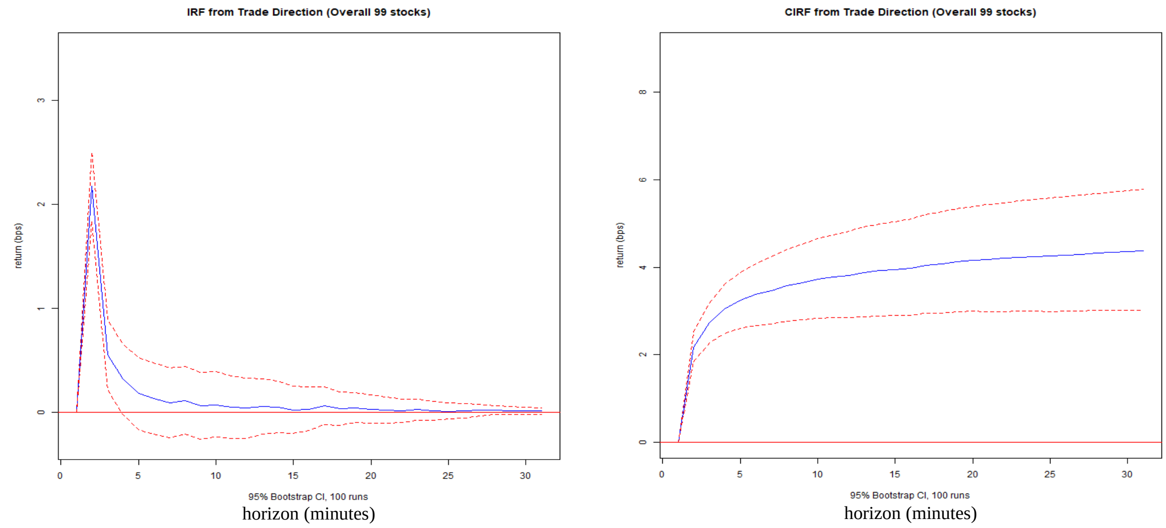
In the study of VAR for each stock, we begin by testing for unit root (non-stationary) using the Augmented Dickey-Fuller (ADF) test, which confirms the presence of stationarity (a less than 0.05 p-value) for both variables (trade direction and returns of quote midpoint changes) before selecting the VAR model based on the lag selection of the AIC in the proper consideration of the model fit. Secondly, the diagnostic test on the residual of the fitted model is applied as the test for serial correlation using a Portmanteau test (if a p-value is less than a 5% significant level, there is the presence of serial correlation).

Next, the test for heteroscedasticity in the residual using a multivariate ARCH Lagrange-Multiplier test is applied (serial correlation is present if a p-value is less than 5% significant level). The stability test is then examined, and the distribution of the residuals is considered by using a normality test (the fitted models are normally distributed as long as a p-value is greater than 0.05). Finally, this study includes 95% confidence intervals in the IRF and the CIRF. The forecast horizon in the market events concerning the trade direction and the changes of quote midpoints (returns of quote midpoint changes) is depicted on the x-axis (0-30 market events in a minute). On the y-axis, the IRF and the CIRF are illustrated in number and converted to bps by multiplying by 10,000.

The IRF results show that a unit positive shock of the trade direction has a positive effect on the returns of quote midpoint changes. Even though there are some negative shocks on the returns of quote midpoint changes, the majority are positive. The CIRF, a permanent price impact during 30 market events, implies that trade-correlated information increases at 30 events in a minute. After that, the trade impacts level off, confirming the selected lag length based on the AIC.

In Figure 1.5, the IRF of the 98 stocks, on average, reaches the highest value at 2.18 bps and then sharply decreases to 0.56 bps at the 2nd event, after that the IRF gradually decrease to 0.01 at the 30th event, and the CIRF of the 98 stocks, on average, level off at around 4.40 bps at the 30th event.

Figure 1.5: Average Values of Impulse Response Function (IRF)
and Cumulative Impulse Response Function (CIRF)



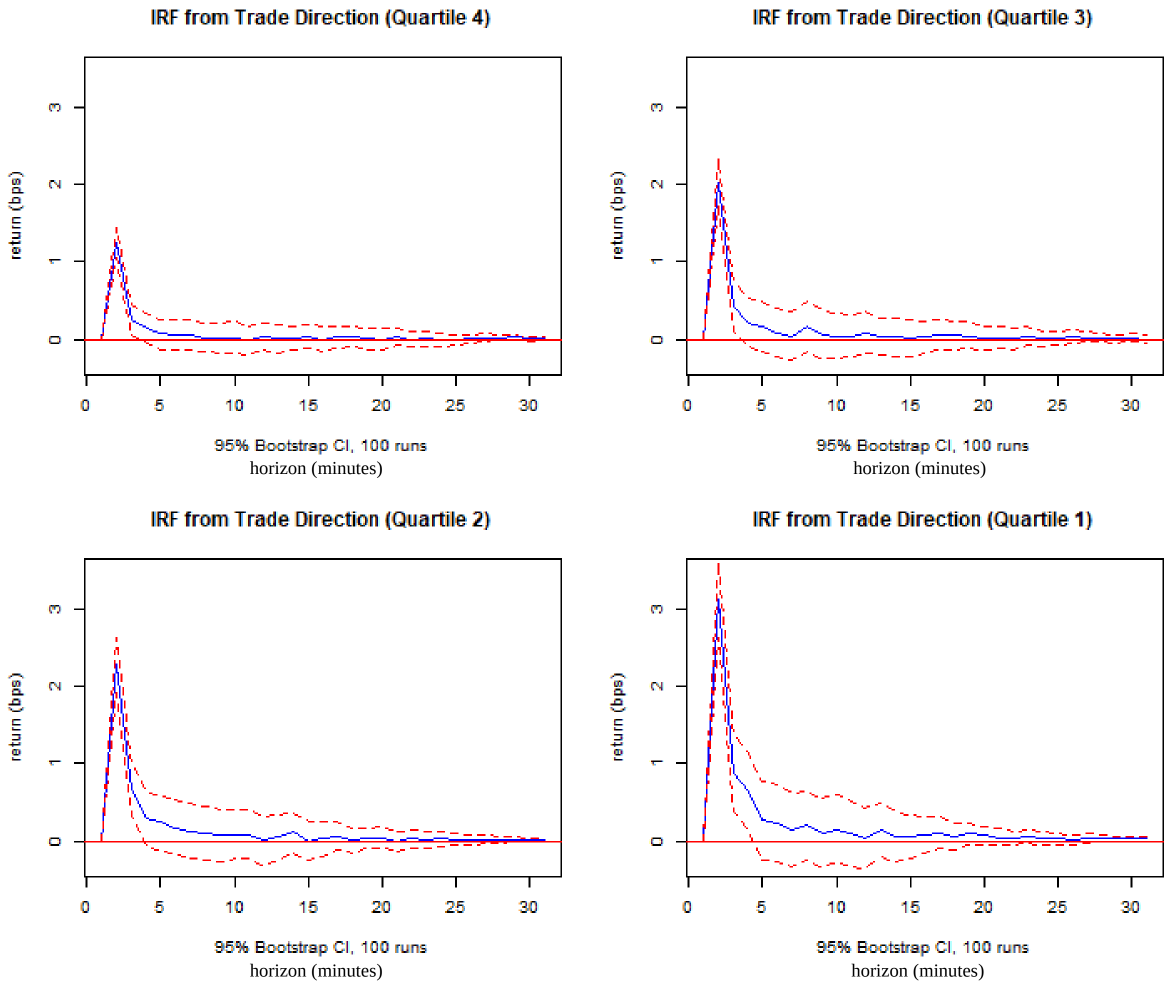
Notes: This figure is reported using the sample observations incorporating the 98 stocks comprising the SET100 index in a 1-minute horizon by generating bootstrap residuals for 100 times (the solid blue line) with the 95% confidence interval (the dotted red lines) from the resampling distribution.

In Figure 1.6, the IRF of MCap quartiles 4, 3, 2, and 1, on average, reach the highest value at around 1.25, 2.02, 2.27 and 3.12 bps, respectively, and then gradually decrease to almost 0.00 bps at the 30th event. In Figure 1.7, the CIRF of MCap quartiles 4, 3, 2, and 1, on average, level off at around 2.16, 3.70, 4.65 and 6.88 bps, respectively. These results suggest that the amount of trade-correlated information is clearly impounded much higher in MCap quartile 1 than 4. These findings suggest that the higher value firms have less price impact and information asymmetry than lower value firms. These results are consistent with the findings of different spread measures in Table 1.4, Hasbrouck (1991b), and Easley et al. (1996). These results also align with the findings of Riordan and Storkenmeir (2012) and confirm that price efficiency decreases across the MCap quartiles from 4 to 1. Liquidity suppliers are less able to avoid informed trades and incur larger adverse selection costs when trading in stocks in lower MCap quartiles.

In summary, these findings indicate that information is contained in trades, exhibiting the existence of information asymmetry and significantly impacting intraday price discovery.

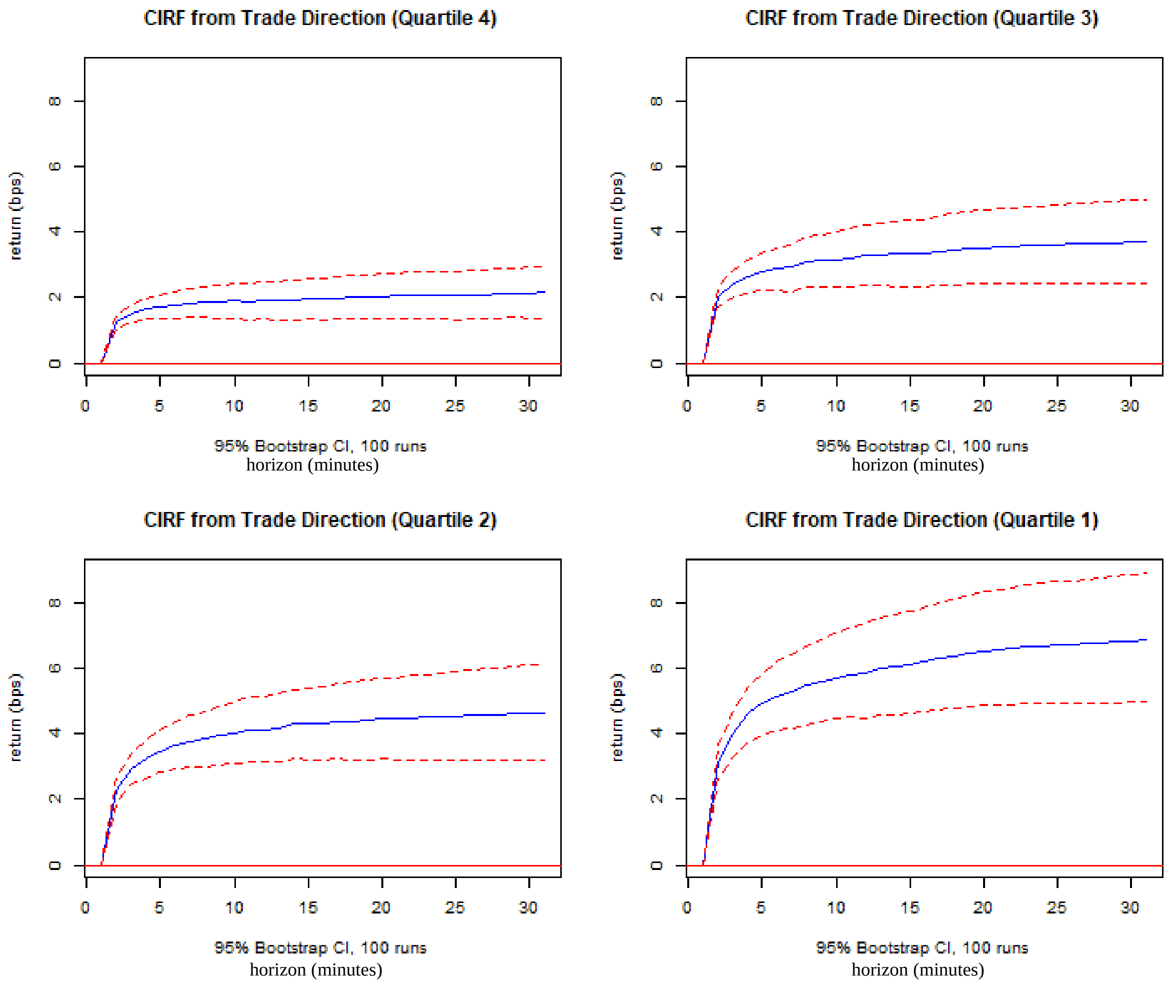
This trade-correlated information also has a greater price impact on trades across the lower Mcap quartiles, indicating a higher information asymmetry across the lower-value stocks.

Figure 1.6: Average Values of Impulse Response Function (IRF)



Notes: This figure is reported using the sample observations incorporating the 98 stocks comprising the SET100 index with different market capitalisations categorised into four quartiles in a 1-minute horizon by generating bootstrap residuals for 100 times (the solid blue line) with the 95% confidence interval (the dotted red lines) from the resampling distribution

Figure 1.7: Average Values of Cumulative Impulse Response Function (CIRF)



Notes: This figure is reported using the sample observations incorporating the 98 stocks comprising the SET100 index with different market capitalisations categorised into four quartiles in a 1-minute horizon by generating bootstrap residuals for 100 times (the solid blue line) with the 95% confidence interval (the dotted red lines) from the resampling distribution

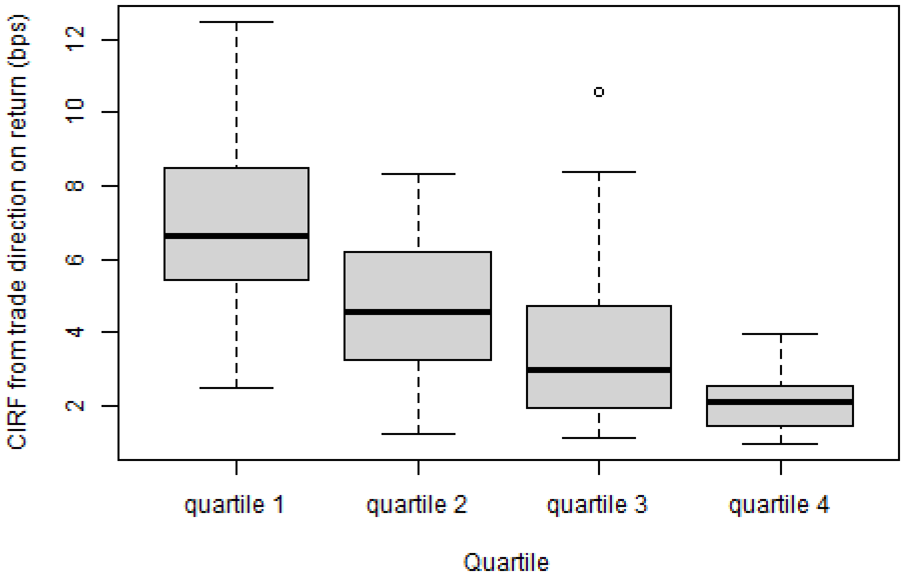
Figure 1.8 represents a boxplot displaying the distribution of the values of the CIRF of 98 stocks at the 30th event in four quartiles and comparing values of the CIRF of 98 stocks with different market capitalisations categorised into four quartiles.

It can be seen that the median values of the CIRF of 98 stocks with four different MCap quartiles have clearly different patterns. These differences indicate that median values of the CIRF are negatively correlated with the level of MCap quartiles. These findings suggest that the lower the MCap quartiles are, the higher the median values of the CIRF are.

Table 1.6 reports the Welch one-way test (one-way ANOVA test relaxing the homogeneity of variance assumption). The results confirm significant differences between means of the CIRF across four MCap quartiles. We then conduct pairwise comparisons using a t-test that relaxes the homogeneity of variance assumption. Evidence shows that the mean values of the CIRF of stocks in MCap quartile 4 are statistically significantly different from those in MCap quartiles 1-3. The mean values of the CIRF of MCap quartiles 2-3 are also significantly different from those in MCap quartile 1.

Therefore, we can use the findings above from Figure 1.8 and Table 1.6 to help confirm the conclusion we draw from Figures 1.6 and 1.7 that the amount of trade-correlated information is impounded much lower in the stocks with higher market capitalisations than in the stocks with lower market capitalisations, and lower value firms have more price impact and asymmetric information than higher value firms.

Figure 1.8: Boxplots Illustrating the Median Values and the Spread of the Values of the CIRF



Notes: This figure is reported using the sample observations incorporating the 98 stocks comprising the SET100 index at the 30th event with different market capitalisations categorised into four quartiles in a 1-minute horizon.

Table 1.6: ANOVA Test of CIRF in Four Different MCap Quartiles

Variables	Quartile 4 (Mean)	Quartile 3 (Mean)	Quartile 2 (Mean)	Quartile 1 (Mean)	ANOVA (p-value)	Statistically significant difference between four quartiles
CIRF	2.15	3.70	4.65	6.88	3.19×10^{-12}	Yes
No. of Stocks	24	25	25	25		
Observations	457,048	352,360	323,375	274,120		1,406,903
Pairwise Comparison					t-test (p-value)	Statistically significant difference between two quartiles
Quartiles 4 and 3					0.0045	Yes
Quartiles 4 and 2					2.80×10^{-6}	Yes
Quartiles 4 and 1					3.40×10^{-9}	Yes
Quartiles 3 and 2					0.1215	No
Quartiles 3 and 1					$5..00\times10^{-5}$	Yes
Quartiles 2 and 1					0.0013	Yes

1.5.2.3 The Effect of Market-wide and Stock-level Factors on Trade via Spread Measures: Price Impact

Table 1.7 below reports the estimated coefficients of our panel regression analysis of equations (1.16) – (1.27) or models (1) – (12). The coefficients explain what happened to the price impact.

The turnover ratio of stocks and the index returns are statistically significant and positive for all models, which makes the turnover ratio of stocks and the index returns an independent variable for the entire sample. The coefficients of the turnover ratio of stocks for our data samples are 0.43, 0.42, 0.42, 0.45, 0.42, 0.45, and 0.44, respectively. The coefficients of the index returns for our data samples are 0.55, 0.50, 0.50,0.45, and 0.66, respectively. The turnover ratio of stocks is statistically significant and positive across all four MCap quartiles. The index returns are also statistically significant and positive across all four MCap quartiles, except MCap quartile 4. This finding could indicate that trades tend to exert more influence over prices if the index returns increase. The results are in line with the findings of Amihud (2002), Amihud et al. (2015) and Chiang and Zheng (2015), which confirm the positive relationship between stock excess returns and illiquidity. However, increased index returns do not affect the price impact of trades over stocks in MCap quartile four because they are the most liquid stocks in our data sample. As supported by the findings of Healy and Palepu (2001) and Diamond and Verrechia (1991), reducing information asymmetry can proceed by improving corporate disclosure practices (Healy and Palepu (2001). Large market capitalisation firms are more likely to reveal more information to the public regarding corporate disclosures, convinced by obtaining more benefits from a decreased information asymmetry. Thus, they can convince larger investors like institutional investors to trade, resulting in increased liquidity and reduced price impact of trades (Diamond and Verrechia, 1991). This finding could also indicate that trades tend to exert more influence over prices if the turnover ratio of stocks increases, which is consistent with the findings of Lee and Swanminathon (2000), Chiyachantana et al. (2004), and Spierdijk (2004) that there is evidence of the positive relationship between turnover and price impact of trades. This phenomenon may result from the specific character of the SET with a relatively high proportion rate of retail traders (or individual traders), supported by the evidence shown in Tables 1.2 and 1.3. These traders meet challenges in handling significant transactions and providing liquidity.

The market capitalisation is statistically significant and negative for all models, which include them as independent variables in the overall data sample and across all four MCap quartiles. The coefficients of the market capitalisation for our data samples are -12.67, -12.41, -13.36, -13.16, and -14.18, respectively. Therefore, we found evidence that there is a negative relationship between market capitalisation and the price impact of trades. These results indicate that during favourable market conditions, such as a bullish market with a relatively high market capitalisation, there is a reduction in the price impact of trades.

The realised volatility is statistically significant and positive for all models except model (12). The coefficients for our data samples are 0.26, 0.22, 0.21, 0.20, 0.18 and 0.15, respectively. This tendency also arises across all four MCap quartiles, except MCap quartile 4. These findings may suggest that the effect of volatility, proxied by the realised volatility, will disappear if the SET sees an increase in the index returns, market capitalisation, and turnover ratio of stocks simultaneously.

To sum up, when the market-wide and stock-level factors reflect favourable market conditions, like bullish markets exhibiting high market capitalisation, the turnover ratio of stocks and the index returns increase the price impact of trades due to the high proportion of individuals in the SET with lower liquidity, reflecting the higher illiquidity risk. The realised volatility, indicating the market volatility in the SET, plays a role in influencing the higher price impact of trades. However, if the SET simultaneously sees a positive index returns, a larger market capitalisation, and a higher turnover of trading activity in stocks, the effect of market volatility will be mitigated.

Table 1.7: Panel Regression Analysis of Price Impact (Random Effects)

	Random Effect											
	Dependent Variable: Price Impact											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overall												
intercept	2.09****	1.96****	2.14****	8.74****	1.91****	2.09****	8.55****	1.95****	8.88****	1.90****	8.74****	9.27****
(std. error)	(0.12)	(0.11)	(0.11)	(0.54)	(0.11)	(0.12)	(0.54)	(0.11)	(0.54)	(0.11)	(0.54)	(0.54)
realised volatility	0.26****				0.22****	0.21****	0.20***			0.18***	0.15**	0.09
(std. error)	(0.06)				(0.06)	(0.06)	(0.06)			(0.06)	(0.06)	(0.06)
stock turnover ratio		0.43****			0.42****			0.42****	0.45****	0.42****	0.45****	0.44****
(std. error)		(0.03)			(0.03)			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
return of SET index			0.55****			0.50****		0.50****		0.45****		0.66****
(std. error)			(0.10)			(0.10)		(0.10)		(0.10)		(0.10)
ln(MCap. of SET)				-12.67****			-12.41****		-13.36****		-13.16****	-14.18****
(std. error)				(1.02)			(1.02)		(1.01)		(1.01)	(1.02)
R-squared	0.001	0.013	0.003	0.013	0.014	0.004	0.014	0.015	0.028	0.016	0.028	0.032
Adj. R-squared	0.001	0.013	0.003	0.013	0.014	0.003	0.014	0.015	0.028	0.016	0.028	0.032
Chi-squared	17.65	159.43	30.54	155.15	171.94	42.06	166.04	184.98	336.25	192.83	342.60	387.53
(p-value)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
4Q MCap												
intercept	1.19****	0.98****	1.25****	5.42****	0.94****	1.19****	5.23****	0.98****	5.06****	0.94****	4.92****	5.03****
(std. error)	(0.11)	(0.09)	(0.11)	(0.55)	(0.09)	(0.11)	(0.55)	(0.09)	(0.54)	(0.09)	(0.54)	(0.55)
realised volatility	0.24****				0.19***	0.23****	0.20***			0.18***	0.15**	0.14**
(std. error)	(0.06)				(0.06)	(0.07)	(0.06)			(0.06)	(0.06)	(0.06)
stock turnover ratio		0.73****			0.72****			0.73****	0.73****	0.72****	0.71****	0.71****
(std. error)		(0.06)			(0.06)			(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
return of SET index			0.15			0.08		0.06		0.01		0.13
(std. error)			(0.10)			(0.10)		(0.10)		(0.10)		(0.10)
ln(MCap. of SET)				-8.03****			-7.77****		-7.84****		-7.66****	-7.86****
(std. error)				(1.04)			(1.04)		(1.02)		(1.02)	(1.04)
R-squared	0.005	0.045	0.0007	0.020	0.048	0.005	0.024	0.045	0.064	0.048	0.066	0.067
Adj. R-squared	0.004	0.045	0.0003	0.020	0.047	0.004	0.023	0.045	0.064	0.047	0.065	0.065
Chi-squared	13.76	136.46	1.89	59.20	145.44	14.42	69.38	136.78	197.91	145.41	203.94	205.70
(p-value)	(0.0002)	(<0.0001)	(0.17)	(<0.0001)	(<0.0001)	(0.0007)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
3Q MCap												
intercept	1.97****	1.89****	1.97****	7.48****	1.87****	1.96****	7.45****	1.87****	7.65****	1.87****	7.64****	8.24****
(std. error)	(0.22)	(0.23)	(0.22)	(1.04)	(0.23)	(0.22)	(1.05)	(0.23)	(1.04)	(0.23)	(1.05)	(1.06)
realised volatility	0.09				0.07	0.03	0.04			0.01	0.02	-0.06
(std. error)	(0.12)				(0.12)	(0.12)	(0.12)			(0.12)	(0.12)	(0.12)
stock turnover ratio		0.26****			0.26**			0.25****	0.29****	0.25****	0.29****	0.28****
(std. error)		(0.07)			(0.07)			(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
return of SET index			0.61***			0.61***		0.59***		0.58***		0.76****
(std. error)			(0.19)			(0.19)		(0.19)		(0.19)		(0.19)
ln(MCap. of SET)				-10.58****			-10.54****		-11.13****		-11.11****	-12.28****
(std. error)				(1.96)			(1.97)		(1.96)		(1.97)	(1.99)
R-squared	1.79×10^{-4}	0.005	0.004	0.010	0.005	0.004	0.010	0.008	0.016	0.008	0.016	0.021
Adj. R-squared	-1.69×10^{-4}	0.004	0.003	0.010	0.004	0.0003	0.009	0.007	0.015	0.007	0.015	0.020
Chi-squared	0.51	13.58	10.25	29.02	13.93	10.30	29.11	23.02	45.88	23.03	45.88	61.50
(p-value)	(0.47)	(0.0002)	(0.001)	(<0.0001)	(0.0009)	(0.006)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
2Q MCap												
intercept	2.18****	1.97****	2.25****	7.58****	1.90****	2.18****	7.32****	1.95****	8.07****	1.90****	7.87****	8.35****
(std. error)	(0.18)	(0.18)	(0.17)	(1.09)	(0.18)	(0.18)	(1.09)	(0.18)	(1.08)	(0.18)	(1.08)	(1.09)
realised volatility	0.33***				0.26**	0.28**	0.28**			0.22*	0.20	0.14
(std. error)	(0.13)				(0.13)	(0.13)	(0.13)			(0.13)	(0.13)	(0.13)
stock turnover ratio		0.73****			0.72****			0.72****	0.78****	0.71****	0.77****	0.77****
(std. error)		(0.09)			(0.09)			(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
return of SET index			0.54***			0.47**		0.48**		0.43**		0.61***
(std. error)			(0.20)			(0.20)		(0.20)		(0.20)		(0.20)
ln(MCap. of SET)				-10.23****			-9.88****		-11.79****		-11.51****	-12.45****
(std. error)				(2.07)			(2.07)		(2.05)		(2.06)	(2.08)
R-squared	0.002	0.020	0.002	0.008	0.021	0.004	0.010	0.022	0.031	0.023	0.031	0.034
Adj. R-squared	0.002	0.020	0.002	0.008	0.021	0.003	0.009	0.021	0.030	0.022	0.030	0.033
Chi-squared	6.69	60.82	7.25	24.45	65.20	12.09	29.42	66.66	94.41	69.71	97.06	106.25
(p-value)	(0.01)	(<0.0001)	(0.007)	(<0.0001)	(<0.0001)	(0.0024)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
1Q MCap												
intercept	2.98****	2.83****	3.06****	14.28****	2.75****	2.98****	14.02****	2.81****	14.51****	2.75****	14.31****	15.19****
(std. error)	(0.23)	(0.23)	(0.23)	(1.39)	(0.24)	(0.23)	(1.40)	(0.23)	(1.38)	(0.24)	(1.39)	(1.40)
realised volatility	0.39**				0.32**	0.31*	0.29*			0.25	0.21	0.10
(std. error)	(0.16)				(0.16)	(0.17)	(0.16)			(0.16)	(0.16)	(0.16)
stock turnover ratio		0.37****			0.36****			0.36****	0.40****	0.36****	0.39****	0.39****
(std. error)		(0.06)			(0.06)			(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
return of SET index			0.88****			0.81****		0.82***		0.76***		1.11****
(std. error)			(0.26)			(0.26)		(0.26)		(0.26)		(0.26)
ln(MCap. of SET)				-21.58****			-21.21****		-22.52****		-22.24****	-23.95****
(std. error)				(2.65)			(2.66)		(2.63)		(2.64)	(2.67)
R-squared	0.002	0.013	0.004	0.022	0.014	0.005	0.023	0.016	0.037	0.017	0.037	0.043
Adj. R-squared	0.002	0.013	0.004	0.021	0.014	0.004	0.022	0.016	0.036	0.016	0.036	0.042
Chi-squared	5.68	39.64	11.61	66.23	43.59	15.16	69.48	49.76	113.67	52.08	115.42	134.16
(p-value)	(0.02)	(<0.0001)	(0.0007)	(<0.0001)	(<0.0001)	(0.0005)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Number of Observation												11,760

Remarks: '****' indicates significance at the 0.1% level, '***' indicates significance at the 1% level, '**' indicates significance at the 5% level, '*' indicates significance at the 10% level. Robust t-statistic are reported in parentheses.

Notes: This panel regression analysis of price impact employs the daily mean of data in each trading day in a 1-minute horizon.

1.5.2.4 The Effect of Market-wide and Stock-level Factors on Trade via Spread Measures: the Quoted Spread

Table 1.8 reports the estimated coefficients of our panel regression analysis of equations (1.16) – (1.27) or models (1) – (12). The coefficients explain what happened to the quoted spread.

The turnover ratio of stocks is statistically significant and positive for all models. The coefficients for our data samples are 0.55, 0.54, 0.60, 0.60, 0.58, 0.60, and 0.63, respectively. The turnover ratio of stocks is also statistically significant and positive across all four MCap quartiles. This finding could indicate that the bid-ask spread grows wider as the turnover ratio of stocks increases. This result indicates that transaction costs increase and market depth is shallower. This result may occur because of the specific character of the SET with the presence of many retail traders (or individual traders). They face challenges in managing substantial transactions and supplying liquidity during the increased turnover of trading activity.

The index returns and the market capitalisation are statistically significant and negative for all models, which include them as independent variables, and for the overall data sample and across all four MCap quartiles, except MCap quartile 4 for the market capitalisation. The coefficients of the index returns for our data samples are -3.66, -3.83, -3.74, -3.89 and -3.49, respectively. The coefficients of the market capitalisation for our data samples are -31.97, -31.76, -32.88, -32.76, and -27.41, respectively. Therefore, we found evidence of a negative relationship between the index returns and trades via the quoted spread, and another negative relationship between market capitalisation and trade via the quoted spread. These findings indicate that the trading cost is lower as the index returns and/or market capitalisation is higher. These findings may suggest increased investor confidence in stocks with higher index returns (and/or larger market capitalisation) because they confidently expect that they will get higher expected returns in trading. As a result, they compete to submit their orders near the currently executed stock price, resulting in a narrower quote of the bid-ask spread and a reduction in transaction cost.

Table 1.8: Panel Regression Analysis of Quoted Spread (Random Effects)

Random Effect												
Dependent Variable: Quoted Spread												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overall												
intercept	32.37****	32.20****	32.59****	49.04****	32.13****	32.41****	48.89****	32.31****	49.24****	32.16****	49.15****	46.39****
(std. error)	(1.02)	(1.03)	(1.02)	(1.65)	(1.03)	(1.02)	(1.65)	(1.03)	(1.65)	(1.03)	(1.66)	(1.66)
realised volatility	0.31**				0.25*	0.68****	0.16			0.63****	0.09	0.46***
(std. error)	(0.15)				(0.15)	(0.15)	(0.15)			(0.15)	(0.15)	(0.15)
stock turnover ratio		0.55****			0.54****			0.60****	0.60****	0.58****	0.60****	0.63****
(std. error)		(0.08)			(0.08)			(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
return of SET index			-3.66****			-3.83****		-3.74****		-3.89****		-3.49****
(std. error)			(0.24)			(0.24)		(0.24)		(0.24)		(0.25)
ln(MCap. of SET)				-31.97****			-31.76****		-32.88****		-32.76****	-27.41****
(std. error)				(2.49)			(2.50)		(2.49)		(2.50)	(2.51)
R-squared	0.0003	0.004	0.019	0.014	0.004	0.021	0.014	0.023	0.018	0.025	0.018	0.035
Adj. R-squared	0.0003	0.003	0.019	0.014	0.004	0.021	0.014	0.023	0.018	0.025	0.018	0.034
Chi-squared	4.10	41.42	229.66	164.50	44.19	249.82	165.62	282.02	216.42	299.17	216.79	421.86
(p-value)	(0.04)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
4Q MCap												
intercept	25.89****	25.59****	26.06****	29.01****	25.55****	25.92****	28.78****	25.65****	28.51****	25.54****	28.36****	25.82****
(std. error)	(1.75)	(1.78)	(1.75)	(2.91)	(1.78)	(1.75)	(2.92)	(1.78)	(2.93)	(1.78)	(2.94)	(2.94)
realised volatility	0.27				0.20	0.57**	0.25			0.49*	0.17	0.49*
(std. error)	(0.27)				(0.27)	(0.27)	(0.27)			(0.27)	(0.27)	(0.28)
stock turnover ratio		1.00****			0.98****			1.13****	0.99****	1.10****	0.98****	1.10****
(std. error)		(0.28)			(0.28)			(0.28)	(0.28)	(0.28)	(0.28)	(0.28)
return of SET index			-2.88****			-3.02****		-3.01****		-3.13*****		-3.12****
(std. error)			(0.43)			(0.44)		(0.43)		(0.44)		(0.44)
ln(MCap. of SET)				-5.87			-5.56		-5.62		-5.40	-0.55
(std. error)				(4.48)			(4.49)		(4.47)		(4.48)	(4.50)
R-squared	3.42×10^{-4}	0.004	0.015	5.97×10^{-4}	0.005	0.017	8.74×10^{-4}	0.021	0.005	0.022	0.005	0.022
Adj. R-squared	-5.62×10^{-6}	0.004	0.014	2.49×10^{-4}	0.004	0.016	1.80×10^{-4}	0.020	0.004	0.021	0.004	0.021
Chi-squared	0.98	12.93	44.46	1.72	13.46	48.74	2.52	61.65	14.52	64.95	14.92	64.94
(p-value)	(0.32)	(0.0003)	(<0.0001)	(0.19)	(0.001)	(<0.0001)	(0.28)	(<0.0001)	(0.0007)	(<0.0001)	(0.002)	(<0.0001)
3Q MCap												
intercept	30.53****	30.37****	30.74****	52.58****	30.33****	30.58****	52.59****	30.50****	52.97****	30.36****	53.02****	49.87****
(std. error)	(1.91)	(1.91)	(1.91)	(2.98)	(1.91)	(1.91)	(2.99)	(1.91)	(2.98)	(1.91)	(2.99)	(2.98)
realised volatility	0.19				0.16	0.62**	-0.01			0.59**	-0.06	0.36
(std. error)	(0.27)				(0.27)	(0.27)	(0.27)			(0.27)	(0.27)	(0.27)
stock turnover ratio		0.53****			0.53****			0.60****	0.64****	0.59****	0.64****	0.68****
(std. error)		(0.16)			(0.16)			(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
return of SET index			-4.33****			-4.48****		-4.39****		-4.54****		-3.98****
(std. error)			(0.43)			(4.43)		(0.43)		(0.43)		(0.43)
ln(MCap. of SET)				-42.40****			-42.42****		-43.63****		-43.70****	-37.59****
(std. error)				(4.40)			(4.42)		(4.40)		(4.42)	(4.40)
R-squared	1.65×10^{-4}	0.004	0.034	0.031	0.004	0.036	0.031	0.039	0.037	0.041	0.037	0.065
Adj. R-squared	-1.82×10^{-4}	0.003	0.034	0.031	0.003	0.036	0.031	0.039	0.036	0.040	0.036	0.063
Chi-squared	0.47	11.04	102.63	92.80	11.37	108.06	92.77	117.48	109.73	112.44	109.74	198.50
(p-value)	(0.49)	(0.0009)	(<0.0001)	(<0.0001)	(0.003)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
2Q MCap												
intercept	34.96****	34.77****	35.16****	47.64****	34.70****	34.99****	47.45****	34.86****	48.12****	34.72****	48.00****	45.40****
(std. error)	(1.61)	(1.64)	(1.61)	(3.26)	(1.64)	(1.61)	(3.28)	(1.64)	(3.27)	(1.64)	(3.29)	(3.30)
realised volatility	0.32				0.26	0.66**	0.20			0.60*	0.13	0.47
(std. error)	(0.33)				(0.34)	(0.34)	(0.33)			(0.34)	(0.34)	(0.34)
stock turnover ratio		0.66***			0.65**			0.73***	0.77***	0.70***	0.76***	0.79***
(std. error)		(0.25)			(0.25)			(0.25)	(0.25)	(0.25)	(0.25)	(0.25)
return of SET index			-3.38****			-3.55****		-3.45****		-3.59****		-3.29****
(std. error)			(0.53)			(0.54)		(0.53)		(0.54)		(0.54)
ln(MCap. of SET)				-24.28****			-24.02****		-25.82****		-25.64****	-20.59****
(std. error)				(5.47)			(5.48)		(5.48)		(5.50)	(5.53)
R-squared	2.99×10^{-4}	0.002	0.013	0.007	0.002	0.015	0.007	0.016	0.010	0.017	0.010	0.022
Adj. R-squared	-3.44×10^{-5}	0.002	0.013	0.006	0.002	0.014	0.006	0.016	0.009	0.016	0.009	0.020
Chi-squared	0.90	6.77	40.84	19.74	7.36	44.75	20.10	49.32	29.01	52.55	29.14	66.64
(p-value)	(0.34)	(0.009)	(<0.0001)	(<0.0001)	(0.025)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
1Q MCap												
intercept	37.78****	37.58****	38.05****	66.28****	37.49****	37.82****	66.09****	37.71****	66.57****	37.52****	66.48****	63.63****
(std. error)	(2.11)	(2.13)	(2.11)	(3.49)	(2.13)	(2.11)	(3.51)	(2.13)	(3.50)	(2.13)	(3.51)	(3.52)
realised volatility	0.46				0.37	0.87***	0.20			0.79**	0.10	0.47
(std. error)	(0.33)				(0.33)	(0.33)	(0.33)			(0.33)	(0.33)	(0.33)
stock turnover ratio		0.46****			0.45****			0.50****	0.53****	0.48****	0.53****	0.55****
(std. error)		(0.12)			(0.12)			(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
return of SET index			-4.05****			-4.26****		-4.14****		-4.33****		-3.59****
(std. error)			(0.53)			(0.53)		(0.52)		(0.53)		(0.53)
ln(MCap. of SET)				-54.68****			-54.43****		-55.94****		-55.81****	-50.29****
(std. error)				(5.37)			(5.38)		(5.36)		(5.38)	(5.40)
R-squared	6.31×10^{-4}	0.005	0.019	0.033	0.005	0.022	0.034	0.025	0.040	0.027	0.040	0.054
Adj. R-squared	2.98×10^{-4}	0.004	0.019	0.033	0.004	0.021	0.033	0.024	0.039	0.026	0.039	0.053
Chi-squared	1.89	14.06	59.35	103.83	15.32	66.31	104.19	76.73	123.60	82.46	123.65	171.67
(p-value)	(0.17)	(0.0002)	(<0.0001)	(<0.0001)	(0.0005)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Number of Observation												11,760

Remarks: '****' indicates significance at the 0.1% level, '***' indicates significance at the 1% level, '**' indicates significance at the 5% level, '*' indicates significance at the 10% level. Robust t-statistic are reported in parentheses.

Notes: This panel regression analysis of quoted spread employs the daily mean of data in each trading day in a 1-minute horizon.

1.5.2.5 The Effect of Market-wide and Stock-level Factors on Trade via Spread Measures: the Effective Spread and the Realised Spread

Table 1.9 and Table 1.10 report the estimated coefficients of our panel regression analysis of equations (1.16) – (1.27) or models (1) – (12). Table 1.9 and Table 1.10 present the coefficients explaining what happened to the effective and realised spread, respectively.

The turnover ratio of stocks is statistically significant and negative for all models, which puts the turnover ratio as an independent variable for the entire observation, and across each MCap quartile (except the third quartile) in Tables 1.9 and 1.10. The coefficients for our observations in Table 1.9 are -0.42, -0.43, -0.43, -0.41, -0.43, -0.41 and -0.41, respectively. The coefficients for our observations in Table 1.10 are -0.85, -0.84, -0.85, -0.86, -0.84, -0.85 and -0.85, respectively. This finding could indicate that trade tends to exert more effect on the transaction cost of liquidity demanders if the stocks' turnover ratio increases, since this effective spread is paid by liquidity demanders (Riordan and Storkenmaier, 2012). This finding could also indicate that trade tends to exert more influence on the revenue of liquidity suppliers because this realised spread is the liquidity suppliers' revenue. The effective spread consists of two components: the realised spread (the revenue of liquidity suppliers) and the price impact (the adverse selection cost). Therefore, as the stocks' turnover ratio increases, the effective spread and the realised spread will be narrower. In other words, transaction costs paid by liquidity demanders will decrease when the turnover ratio increases. However, the revenue of liquidity suppliers will fall when the turnover ratio of stocks increases. As mentioned, there are many individual traders in the SET; they typically act like liquidity suppliers who provide liquidity to the market by mainly submitting limit orders. Therefore, these findings suggest that the liquidity suppliers or individual traders find it more difficult to manage adverse selection risk during the higher turnover ratio in traded stocks. An increased price impact of trade also supports this evidence, as the traded stocks have a higher turnover ratio, as shown in Table 1.7.

By contrast, in Table 1.9, the market capitalisation is statistically significant and negative for all models, including them as independent variables, and for the overall data sample and the MCap quartiles 3 and 1. The coefficients of the market capitalisation for our data samples are -9.38, -9.44, -8.76, -8.77, and -9.48, respectively. Therefore, we found evidence of a negative relationship between market capitalisation and the effective spread.

These findings show that this spread, paid by liquidity demanders, will decrease when the SET's market capitalisation increases.

In Table 1.10, the market capitalisation are statistically significant and positive for the last three models, including them as independent variables, and for the overall data sample and the MCap quartiles 4 and 2. The coefficients of the market capitalisation for our data samples in Table 1.10 are 4.60, 4.39 and 4.69, respectively. Therefore, we found evidence of a positive relationship between market capitalisation and the realised spread. These findings show that liquidity suppliers' revenue will increase when the market capitalisation increase in the SET. Therefore, as the SET’s market capitalisation increases, the effective spread will be narrower, but the realised spread will be higher. In other words, during favourable market conditions, such as bullish markets with increased market capitalisations, there will be a decrease in transaction costs paid by liquidity demanders but an increase in the revenue of liquidity suppliers. These findings also indicate that liquidity demanders can reduce their transaction costs. Liquidity suppliers can also avoid being adversely selected during the higher market capitalisation in the SET, and increase their revenue. The decreased price impact of trade supports this evidence, as the SET has a greater market capitalisation, as shown in Table 1.7.

The index returns are statistically significant and positive for model (12), which puts the index returns as an independent variable for the whole observation and MCap quartile one and all models in only MCap quartile 2 in Table 1.9. However, the index returns are insignificant for all models, which puts the index returns as an independent variable for the entire observation but is significantly negative for all models in only MCap quartile 3 in Table 1.10. The coefficient for model (12) for our data sample in Table 1.9 is 0.47. These findings could indicate that when the market sees an increasing turnover ratio and a higher level of market capitalisation simultaneously, the trade tends to exert more effect on the transaction cost of the liquidity demanders if the index returns increase. Such instances occur probably because of many retail traders (or individual traders) in the Thai stock market. They struggle to provide liquidity to the market, leading to a higher level of market illiquidity during the increased share turnover ratio and larger market capitalisation. Nevertheless, trades do not affect the revenue of liquidity providers.

Table 1.9 Panel Regression Analysis of Effective Spread (Random Effects)

	Random Effects											
	Dependent Variable: Effective Spread											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overall												
intercept	30.83****	31.03****	30.82****	35.70****	31.02****	30.83****	35.75****	31.02****	35.56****	31.02****	35.57****	35.94****
(std. error)	(1.02)	(1.03)	(1.02)	(1.50)	(1.03)	(1.02)	(1.50)	(1.03)	(1.50)	(1.03)	(1.51)	(1.51)
realised volatility	-0.01				0.03	-0.04	-0.05			0.003	-0.008	-0.06
(std. error)	(0.13)				(0.13)	(0.13)	(0.13)			(0.13)	(0.13)	(0.13)
stock turnover ratio		-0.42****			-0.43****			-0.43****	-0.41****	-0.43****	-0.41****	-0.41****
(std. error)		(0.07)			(0.07)			(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
return of SET index			0.27			0.28		0.33		0.33		0.47**
(std. error)			(0.21)			(0.21)		(0.21)		(0.21)		(0.21)
ln(MCap. of SET)				-9.38****			-9.44****		-8.76****		-8.77****	-9.48****
(std. error)				(2.12)			(2.12)		(2.12)		(2.12)	(2.15)
R-squared	4.55×10^{-7}	0.003	0.0002	0.002	0.003	0.0002	0.002	0.003	0.004	0.003	0.004	0.005
Adj. R-squared	-8.46×10^{-5}	0.003	6.61×10^{-5}	0.002	0.003	-1.21×10^{-5}	0.002	0.003	0.004	0.003	0.004	0.005
Chi-squared	0.005	35.11	1.78	19.65	35.18	1.86	19.82	37.66	52.29	37.65	52.29	57.23
(p-value)	(0.94)	(<0.0001)	(0.18)	(<0.0001)	(<0.0001)	(0.39)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
4Q MCap												
intercept	24.46****	24.76****	24.46****	13.41****	24.73****	24.46****	13.27****	24.75****	13.78****	24.73****	13.60****	13.84****
(std. error)	(1.76)	(1.79)	(1.76)	(2.68)	(1.79)	(1.76)	(2.69)	(1.79)	(2.70)	(1.79)	(2.71)	(2.73)
realised volatility	0.05				0.11	2.61×10^{-5}	0.15			0.05	0.21	0.18
(std. error)	(0.24)				(0.24)	(0.24)	(0.24)			(0.25)	(0.24)	(0.24)
stock turnover ratio		-0.77***			-0.78***			-0.80***	-0.75***	-0.80***	-0.76***	-0.78***
(std. error)		(0.24)			(0.24)			(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
return of SET index			0.53			0.53		0.62		0.60		0.29
(std. error)			(0.38)			(0.39)		(0.38)		(0.39)		(0.39)
ln(MCap. of SET)				21.32****			21.52****		21.13****		21.39****	20.94****
(std. error)				(3.91)			(3.92)		(3.90)		(3.91)	(3.96)
R-squared	1.59×10^{-5}	0.003	0.0007	0.010	0.004	6.63×10^{-4}	0.010	0.004	0.014	0.004	0.014	0.014
Adj. R-squared	-3.32×10^{-4}	0.003	0.0003	0.010	0.003	-3.16×10^{-5}	0.010	0.004	0.013	0.003	0.013	0.013
Chi-squared	0.046	10.02	1.91	29.80	10.22	1.91	30.20	12.63	39.47	12.67	40.22	40.77
(p-value)	(0.83)	(0.002)	(0.167)	(<0.0001)	(0.006)	(0.385)	(<0.0001)	(0.002)	(<0.0001)	(0.005)	(<0.0001)	(<0.0001)
3Q MCap												
intercept	29.31****	29.22****	29.26****	42.66****	29.30****	29.32****	43.05****	29.24****	42.71****	29.31****	43.11****	42.96****
(std. error)	(1.93)	(1.93)	(1.93)	(2.74)	(1.93)	(1.93)	(2.74)	(1.93)	(2.74)	(1.93)	(2.75)	(2.76)
realised volatility	-0.30				-0.30	-0.25	-0.43*			-0.25	-0.43*	-0.41*
(std. error)	(0.23)				(0.23)	(0.23)	(0.23)			(0.23)	(0.23)	(0.23)
stock turnover ratio		0.01			0.02			0.02	0.08	0.03	0.09	0.09
(std. error)		(0.14)			(0.14)			(0.14)	(0.13)	(0.14)	(0.13)	(0.13)
return of SET index			-0.63*			-0.57		-0.63*		-0.57		-0.19
(std. error)			(0.37)			(0.37)		(0.37)		(0.37)		(0.37)
ln(MCap. of SET)				-25.88****			-26.42****		-26.03****		-26.59****	-26.30****
(std. error)				(3.73)			(3.74)		(3.74)		(3.75)	(3.80)
R-squared	5.98×10^{-4}	3.25×10^{-6}	0.001	0.016	6.05×10^{-4}	0.001	0.018	0.001	0.017	0.001	0.018	0.018
Adj. R-squared	2.51×10^{-4}	-3.44×10^{-4}	0.001	0.016	-8.98×10^{-5}	0.001	0.017	0.0004	0.016	0.0004	0.017	0.016
Chi-squared	1.72	0.009	2.99	48.05	1.74	4.10	51.56	3.01	48.37	4.14	51.97	52.21
(p-value)	(0.19)	(0.92)	(0.08)	(<0.0001)	(0.42)	(0.13)	(<0.0001)	(0.22)	(<0.0001)	(0.25)	(<0.0001)	(<0.0001)
2Q MCap												
intercept	33.43****	33.74****	33.37****	33.13****	33.75****	33.42****	33.22****	33.71****	32.61****	33.74****	32.62****	33.39****
(std. error)	(1.55)	(1.58)	(1.55)	(2.87)	(1.58)	(1.55)	(2.88)	(1.58)	(2.89)	(1.58)	(2.90)	(2.92)
realised volatility	-0.10				-0.02	-0.19	-0.10			-0.12	-0.01	-0.11
(std. error)	(0.28)				(0.28)	(0.29)	(0.29)			(0.29)	(0.29)	(0.29)
stock turnover ratio		-0.83****			-0.82****			-0.84****	-0.83****	-0.84****	-0.83****	-0.84****
(std. error)		(0.22)			(0.22)			(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
return of SET index			0.88*			0.93**		0.96**		0.98**		0.97**
(std. error)			(0.45)			(0.46)		(0.45)		(0.46)		(0.46)
ln(MCap. of SET)				0.52			0.40		2.18		2.17	0.68
(std. error)				(4.66)			(4.67)		(4.67)		(4.68)	(4.73)
R-squared	3.92×10^{-5}	0.005	0.001	4.19×10^{-6}	0.005	0.001	4.17×10^{-5}	0.006	0.005	0.006	0.005	0.006
Adj. R-squared	-2.94×10^{-4}	0.005	0.001	3.29×10^{-4}	0.004	0.001	-6.26×10^{-4}	0.006	0.004	0.005	0.004	0.005
Chi-squared	0.118	14.69	3.79	0.013	14.70	4.21	0.125	19.18	14.91	19.34	14.91	19.35
(p-value)	(0.73)	(0.0001)	(0.052)	(0.91)	(0.0006)	(0.12)	(0.94)	(<0.0001)	(0.0006)	(0.0002)	(0.002)	(0.0007)
1Q MCap												
intercept	35.81****	36.20****	35.88****	52.97****	36.11****	35.81****	52.84****	36.19****	52.74****	36.10****	52.53****	53.14****
(std. error)	(2.19)	(2.18)	(2.18)	(3.17)	(2.18)	(2.19)	(3.18)	(2.18)	(3.16)	(2.18)	(3.17)	(3.19)
realised volatility	0.30				0.39	0.28	0.15			0.36	0.23	0.15
(std. error)	(0.27)				(0.27)	(0.28)	(0.27)			(0.28)	(0.27)	(0.27)
stock turnover ratio		-0.45****			-0.46****			-0.46****	-0.42****	-0.47****	-0.42****	-0.43****
(std. error)		(0.10)			(0.10)			(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
return of SET index			0.30			0.23		0.38		0.30		0.78*
(std. error)			(0.43)			(0.44)		(0.43)		(0.44)		(0.44)
ln(MCap. of SET)				-32.91****			-32.72****		-31.92****		-31.62****	-32.81****
(std. error)				(4.42)			(4.44)		(4.42)		(4.43)	(4.48)
R-squared	4.06×10^{-4}	0.007	1.55×10^{-4}	0.018	0.007	4.95×10^{-4}	0.018	0.007	0.024	0.008	0.024	0.025
Adj. R-squared	7.21×10^{-5}	0.006	-1.78×10^{-4}	0.018	0.007	-1.72×10^{-4}	0.018	0.006	0.023	0.007	0.023	0.024
Chi-squared	1.22	20.41	0.46	55.31	22.44	1.48	55.59	21.19	72.93	22.89	73.65	76.85
(p-value)	(0.27)	(<0.0001)	(0.50)	(<0.0001)	(<0.0001)	(0.48)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Number of Observation												11,760

Remarks: '****' indicates significance at the 0.1% level, '***' indicates significance at the 1% level, '**' indicates significance at the 5% level, '*' indicates significance at the 10% level. Robust t-statistic are reported in parentheses.

Notes: This panel regression analysis of effective spread employs the daily mean of data in each trading day in a 1-minute horizon.

Table 1.10: Panel Regression Analysis of Realised Spread (Random Effects)

	Random Effect											
	Dependent Variable: Realised Spread											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overall												
intercept	28.74****	29.06****	28.68****	26.96****	29.11****	28.74****	27.20****	29.07****	26.68****	29.11****	26.83****	26.68****
(std. error)	(1.01)	(1.01)	(1.01)	(1.56)	(1.01)	(1.01)	(1.57)	(1.01)	(1.56)	(1.01)	(1.56)	(1.57)
realised volatility	-0.27*				-0.18	-0.25*	-0.26*			-0.17	-0.16	-0.14
(std. error)	(0.14)				(0.14)	(0.14)	(0.14)			(0.14)	(0.14)	(0.14)
stock turnover ratio		-0.85****			-0.84****			-0.85****	-0.86****	-0.84****	-0.85****	-0.85****
(std. error)		(0.08)			(0.08)			(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
return of SET index			-0.28			-0.21		-0.17		-0.13		-0.20
(std. error)			(0.22)			(0.23)		(0.22)		(0.23)		(0.23)
ln(MCap. of SET)				3.30			2.97		4.60**		4.39*	4.69**
(std. error)				(2.30)			(2.31)		(2.29)		(2.30)	(2.33)
R-squared	3.19×10^{-4}	0.010	0.0001	0.0002	0.010	0.0004	0.0005	0.010	0.010	0.010	0.011	0.011
Adj. R-squared	2.34×10^{-4}	0.010	4.36×10^{-5}	8.96×10^{-5}	0.010	0.0002	0.0003	0.010	0.010	0.010	0.010	0.010
Chi-squared	3.75	120.37	1.51	2.05	122.11	4.64	5.41	120.94	124.43	122.43	125.78	126.53
(p-value)	(0.053)	(<0.0001)	(0.22)	(0.15)	(<0.0001)	(0.10)	(0.07)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
4Q MCap												
intercept	23.28****	23.77****	23.21****	8.00***	23.79****	23.27****	8.04***	23.76****	8.72***	23.79****	8.67***	8.79***
(std. error)	(1.76)	(1.79)	(1.76)	(2.74)	(1.78)	(1.76)	(2.75)	(1.78)	(2.74)	(1.78)	(2.75)	(2.77)
realised volatility	-0.19				-0.08	-0.23	-0.05			-0.13	0.06	0.04
(std. error)	(0.25)				(0.25)	(0.25)	(0.25)			(0.25)	(0.25)	(0.25)
stock turnover ratio		-1.49****			-1.48****			-1.51****	-1.46****	-1.50****	-1.46****	-1.47****
(std. error)		(0.25)			(0.25)			(0.25)	(0.25)	(0.25)	(0.25)	(0.25)
return of SET index			0.39			0.44		0.56		0.59		0.15
(std. error)			(0.40)			(0.40)		(0.40)		(0.40)		(0.40)
ln(MCap. of SET)				29.35****			29.29****		28.98****		29.05****	28.81****
(std. error)				(4.04)			(4.06)		(4.02)		(4.03)	(4.08)
R-squared	1.95×10^{-4}	0.012	3.30×10^{-4}	0.018	0.012	6.18×10^{-4}	0.018	0.013	0.029	0.013	0.030	0.030
Adj. R-squared	-1.52×10^{-4}	0.012	-1.76×10^{-5}	0.018	0.011	-7.64×10^{-5}	0.017	0.012	0.029	0.012	0.028	0.028
Chi-squared	0.56	34.88	0.95	52.67	34.97	1.78	52.69	36.87	87.43	37.14	87.45	87.58
(p-value)	(0.45)	(<0.0001)	(0.33)	(<0.0001)	(<0.0001)	(0.41)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
3Q MCap												
intercept	27.34****	27.34****	27.29****	35.18***	27.43****	27.36****	35.61****	27.38****	35.05****	27.44****	35.47****	34.72****
(std. error)	(1.97)	(1.97)	(1.97)	(2.88)	(1.97)	(1.97)	(2.89)	(1.97)	(2.88)	(1.97)	(2.89)	(2.90)
realised volatility	-0.39				-0.37	-0.27	-0.46*			-0.26	-0.45*	-0.35
(std. error)	(0.25)				(0.25)	(0.25)	(0.25)			(0.25)	(0.25)	(0.25)
stock turnover ratio		-0.25*			-0.24*			-0.23	-0.21	-0.23	-0.20	-0.19
(std. error)		(0.15)			(0.15)			(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
return of SET index			-1.25***			-1.18***		-1.22***		-1.16***		-0.95**
(std. error)			(0.39)			(0.40)		(0.39)		(0.40)		(0.40)
ln(MCap. of SET)				-15.30****			-15.88****		-14.89****		-15.48****	-14.02****
(std. error)				(4.05)			(4.06)		(4.06)		(4.07)	(4.11)
R-squared	8.52×10^{-4}	0.001	0.003	0.005	0.002	0.004	0.006	0.004	0.006	0.005	0.007	0.009
Adj. R-squared	5.05×10^{-4}	0.001	0.003	0.005	0.001	0.003	0.005	0.004	0.005	0.004	0.006	0.007
Chi-squared	2.45	2.89	10.00	14.28	5.16	11.19	17.77	12.49	16.38	13.59	19.66	25.27
(p-value)	(0.12)	(0.09)	(0.002)	(0.0002)	(0.076)	(0.004)	(0.0001)	(0.002)	(0.0003)	(0.004)	(0.0002)	(<0.0001)
2Q MCap												
intercept	31.24****	31.78****	31.12****	25.55****	31.84****	31.24****	25.89****	31.76****	24.54****	31.84****	24.74****	25.03****
(std. error)	(1.53)	(1.56)	(1.53)	(3.03)	(1.56)	(1.53)	(3.05)	(1.56)	(3.03)	(1.56)	(3.05)	(3.07)
realised volatility	-0.43				-0.28	-0.47	-0.38			-0.34	-0.21	-0.25
(std. error)	(0.31)				(0.31)	(0.31)	(0.31)			(0.31)	(0.31)	(0.31)
stock turnover ratio		-1.56****			-1.55****			-1.57****	-1.62****	-1.56****	-1.61****	-1.62****
(std. error)		(0.23)			(0.23)			(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
return of SET index			0.34			0.45		0.48		0.56		0.37
(std. error)			(0.49)			(0.50)		(0.49)		(0.49)		(0.50)
ln(MCap. of SET)				10.76**			10.28**		13.99***		13.70***	13.14**
(std. error)				(5.05)			(5.06)		(5.03)		(5.05)	(5.10)
R-squared	6.34×10^{-4}	0.015	1.57×10^{-4}	0.002	0.015	9.11×10^{-4}	0.002	0.015	0.017	0.015	0.018	0.018
Adj. R-squared	3.01×10^{-4}	0.015	-1.76×10^{-4}	0.001	0.015	2.44×10^{-4}	0.001	0.015	0.017	0.015	0.017	0.016
Chi-squared	1.90	45.38	0.47	4.54	46.22	2.73	6.03	46.33	53.22	47.50	53.69	54.21
(p-value)	(0.17)	(<0.0001)	(0.49)	(0.03)	(<0.0001)	(0.026)	(0.05)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
1Q MCap												
intercept	32.83****	33.37****	32.83****	38.68****	33.35****	32.84****	38.81****	33.38****	38.23****	33.36****	38.21****	37.95****
(std. error)	(2.26)	(2.25)	(2.26)	(3.45)	(2.25)	(2.26)	(3.46)	(2.25)	(3.42)	(2.25)	(3.44)	(3.46)
realised volatility	-0.09				0.07	-0.03	-0.14			0.11	0.02	0.05
(std. error)	(0.31)				(0.31)	(0.31)	(0.31)			(0.31)	(0.31)	(0.31)
stock turnover ratio		-0.83****			-0.83****			-0.83****	-0.82****	-0.83****	-0.82****	-0.82****
(std. error)		(0.11)			(0.11)			(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
return of SET index			-0.59			-0.58		-0.44		-0.46		-0.33
(std. error)			(0.49)			(0.49)		(0.49)		(0.49)		(0.50)
ln(MCap. of SET)				-11.32**			-11.51**		-9.38*		-9.35*	-8.84*
(std. error)				(5.03)			(5.04)		(4.99)		(5.01)	(5.06)
R-squared	2.82×10^{-5}	0.018	4.86×10^{-4}	0.002	0.018	4.90×10^{-4}	0.002	0.018	0.019	0.018	0.019	0.019
Adj. R-squared	-3.05×10^{-4}	0.018	1.53×10^{-4}	0.001	0.017	-1.77×10^{-4}	0.001	0.017	0.018	0.017	0.018	0.018
Chi-squared	0.08	54.52	1.46	5.08	54.55	1.47	5.29	55.32	58.10	55.43	58.08	58.52
(p-value)	(0.77)	(<0.0001)	(0.23)	(0.02)	(<0.0001)	(0.48)	(0.07)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Number of Observation												11,760

Remarks: '****' indicates significance at the 0.1% level, '***' indicates significance at the 1% level, '**' indicates significance at the 5% level, '*' indicates significance at the 10% level. Robust t-statistic are reported in parentheses.

Notes: This panel regression analysis of realised spread employs the daily mean of data in each trading day in a 1-minute horizon.

1.6 Conclusion

This study examines how changes in market returns influence the price impact of trades within the Stock Exchange of Thailand (SET). It also investigates how the turnover of stocks and market capitalisation may affect this relationship. This study also delves into the effects of heightened trading activity on intraday liquidity and price discovery. Different spread measures, vector autoregression (VAR), impulse response function (IRF), cumulative impulse response function (CIRF), and panel regression are analysed. We conduct all studies on 98 stocks in the SET100 index and categorise them into four MCap quartiles to investigate their differences.

Generally, the results exhibit low information asymmetry, low transaction cost, and high liquidity, because the SET100 index includes the largest companies in the Thai stock market. The results also indicate that trades have a reduced price impact during favourable market conditions, like bullish markets with relatively high market capitalisation. The results show that when turnover or market returns increase, there is an increase in the price impact. Also, the results show that the bid-ask spread increases as the turnover increases, indicating shallower market depth. These results could be due to the large proportion of individual investors in the Thai stock market.

Chapter 2

Analysis of Order Submission Aggressiveness Among Diverse Participants in the Thai Stock Market

2.1 Introduction

The strategic behaviour of stock market participants plays a crucial role in moulding the operation of the global stock market, as well as the specific markets of emerging economies (Badhani et al., 2023). The interplay of trading activity between different types of participant has different effects based on the proportion of each group and the competence of their trading skills and behaviours. In developed markets, institutional investors have a high presence, i.e. owning 68% and 60% of listed equities in the U.S. and the U.K., respectively (OECD, 2018). By contrast, emerging markets, including the Thai stock market, have a high proportion of individual investors (Phansatan et al., 2012; Padungsaksawasdi, 2020; Badhani et al., 2023). Moreover, the participation of institutional investors in emerging stock markets is meagre compared to their developed counterparts. As of 2017, institutional investors owned around 20% and 13% of the 100 largest market-capitalisation listed firms in emerging markets and the Thai stock market, respectively (OECD, 2018). Individual investors own 14% of the 100 largest market-cap listed firms in the Thai stock market (OECD, 2018). Also, as of 2021, 33% of the market capitalisation of all listed firms in the Thai stock market was owned by individual investors (OECD, 2023).[1]

[1] De la Cruz et al. (2019) use the term ‘other free-float including retail investors’ to include retail/individual/local investors, who are not required to disclose their ownership, and institutional investors, who do not publicly disclose their holdings because they do not exceed the required threshold.

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Institutional investors are considered financially sophisticated because of their access to technology, information, and other resources (Grossman and Stiglitz, 1980; Glosten and Milgrom, 1985; Kyle, 1985; Badhani et al., 2023). Foreign investors are also considered sophisticated investors (Grinblatt and Keloharju, 2000) because they are wealthy, have access to more extensive investment research, and have more practical trading experience (Agudelo et al., 2019). Conversely, individual investors are considered noise traders (Foucault et al., 2011) who act based on their psychological biases, limiting their trading performance (Phansatan et al., 2012). Froot et al. (2001) explain that foreign investors employ information-based and momentum trading strategies. They show evidence that foreign traders take the other side of individual investors' trades and take advantage of individual investors who have less sophisticated trading skills (Barber et al., 2009; Phansatan et al., 2012). However, Agarwal et al. (2009) argue that Indonesian domestic individual investors outperform foreign investors, emphasising the latter's engagement in aggressive trading activities.

The aggressiveness of the order submission depends on the types of orders that traders place, such as limit orders or market/marketable orders. Suppose traders need liquidity or possess superior information. In that case, they will immediately execute their orders by submitting market/marketable orders, indicating that they place orders with the most aggressive ones and are considered liquidity demanders or impatient investors. They also may face unfortunate prices for such immediacy of execution (Chiu et al., 2017). On the other hand, if traders place limit orders at the specified price, they are considered liquidity suppliers or patient investors. They also face a lower level of execution than liquidity demanders. Their orders may be stale, meaning they may not be executed. To be more likely to be executed, they must modify or cancel their existing orders and resubmit orders at a new specified price. Therefore, we can determine the level of order aggressiveness from the least aggressive, as the cancelled orders, to the most aggressive, as the market/marketable orders (Ranaldo, 2004).

Several studies investigate the order submission aggressiveness employed by different types of trader across different markets. Chiu et al. (2017) examine traders' order submission aggressiveness in the Taiwan index futures market. Their findings reveal distinct patterns of trading behaviours among each trader type, while asserting that the comprehensive limit order book is crucial in reshaping the process of traders' decision-making. In another relevant study, Park et al. (2019) argue that the entry of foreign investors with large inflows significantly influences the trading decisions of individual investors, resulting in heightened cognitive biases, particularly the disposition effect, in their behaviours. Duong et al. (2009) investigate the determinants of order aggressiveness of institutional and individual investors, highlighting nuanced distinctions in their order submission aggressiveness across diverse market conditions. Other studies examine the relationship between order submission aggressiveness and various other factors. For instance, Easley and O'Hara (1992) and Ranaldo (2004) find that the average waiting time has a positive association with the level of order aggressiveness. Parlour (1998), Handa et al. (2003), and Ranaldo (2004) find that the depth on the same side of the incoming order has a positive relationship with the level of order aggressiveness. Parlour (1998) and Handa et al. (2003) conclude that the depth on the opposite side of the incoming order has a negative association with the level of order aggressiveness, and the quoted spread has a negative relation to order submission aggressiveness (Foucault, 1999; Handa et al., 2003; Ranaldo, 2004), and transient return volatility has a negative association with the level of order aggressiveness (Handa and Schwartz, 1996; Foucault, 1999; Ranaldo, 2004). Phansatan et al. (2012) examine investors' trading behaviour and performance in the Thai stock market but they do not delve into the order submission aggressiveness of trading activity. The question of the order submission aggressiveness of investors in the Thai stock market and the market condition remains unanswered.

Even though this paper relates to the literature on order submission aggressiveness of traders conditional on the market conditions, the approach of this paper differs from three closely related papers by Ranaldo (2004), Duong et al. (2009) and Chiu et al. (2017). Firstly, Chiu et al. (2017) investigate the order aggressiveness of four groups of traders: individual day traders, individual non-day traders, foreign institutional firms, and proprietary futures firm traders, focusing on the Taiwan index futures market with a few market conditions, mainly relevant to the state of the limit order book. Their primary interest is discovering the trading timing with aggressiveness and patience among trader types. However, this study focuses on the stock market in Thailand, not futures exchanges. The futures market is designed for traders who need hedging to manage their portfolio risk, and the movement of underlying futures prices usually relies on the stock prices or indices in the stock market. Thus, futures and stock market traders may differ in terms of their trading decisions regarding order submission aggressiveness. This study also explores the order aggressiveness of three types of traders: retail, institutional, and foreign, which differ from that of Chiu et al. (2017). This study employs the ordered logit regression, similar to Chiu et al. (2017). However, it employs a level of aggressiveness that is not similar to that of Chiu et al. (2017). They exclude the cancellation of existing orders from the level of aggressiveness, but this study includes the cancelled pending orders. This study believes that cancellation of pending orders is one of the traders' choices that captures the trading aggressiveness, which depends on an unobservable information set and personal preference, as proposed by Ranaldo (2004). One of the three types of traders in this study may take advantage of better sources of information, especially in emerging markets like the Thai stock market, which has a foreign and retail trader as a significant share of trading values. Secondly, Duong et al. (2009) focus on the order submission aggressiveness strategies at only the best quotes of two traders (institutional and individual traders) in the Australian Stock Exchanges (ASX), which is a developed market that typically influences the market by institutional traders with highest trading values, which is not similar to the Thai stock market, which is an emerging market and influence the market by foreign and retail traders. They consider the market conditions to focus mainly on the market depth of the best quotes relevant to order aggressiveness. Our study differs from theirs in that it explores more types of traders and investigates more than one market condition. Lastly, Ranaldo (2004) studied the level of aggressiveness based on market conditions without considering the trader types with fifteen stocks as his sample in the Swiss Exchange, a developed market, to test seven hypotheses proposed by theoretical literature. Our study investigates market conditions similar to those of Ranaldo (2004). However, it explores the order submission aggressiveness of the three types of traders conditional on market conditions with one hundred stocks in the SET100 index in our sample, which is broader than that of Ranaldo (2004). Our sample size would be more appropriate for capturing trading decisions regarding order submission aggressiveness among three trader types in the Thai stock market. Therefore, the results of this study will be different from those of the previous literature because of our difference in detailed methodologies.

Furthermore, although these studies provide many insights, to the best of our knowledge, none explicitly investigates how institutional, foreign, and individual investors dynamically adapt their order submission aggressiveness according to diverse market factors within the broader perspective of the stock market. In addition, this study will address a further novel topic by focusing on the Stock Exchange of Thailand (SET). In this study, a dataset of trading activities is gathered from the Stock Exchange of Thailand (SET). The sample consists of 100 stocks that comprise the SET100 index for six months, from July to December 2019. An ordered logit regression and an analysis of the marginal probabilities are employed to investigate the order submission aggressiveness of different types of investors in the SET and the interlinked nature of their order submission aggressiveness and market conditions. In detail, our ordered logit regression with independent variables of market conditions, dummy variables of three trader types, and interaction terms between market conditions and each trader type helps (i) to capture how the market conditions influence the trading decision without trader types, (ii) to discover who is more or less aggressive among three types of traders in the market as a whole without considering market conditions, and (iii) to discover how aggressive they decide to trade with their order submisssion conditional to each factor of market conditions. Our ordered logit regression also differs from those of Ranaldo (2004), Duong et al. (2009), and Chiu et al. (2017) in that there is no dummy variable of trader types or interaction terms. Duong et al. (2009) and Chiu et al. (2017) separate samples based on each trader type before conducting regression.

According to Harris (1998), gaining insight into the market conditions influencing order submission aggressiveness helps traders optimise their trading strategies, resulting in reduced transaction costs and increased portfolio returns. Thus, our study can learn how order submission aggressiveness is implemented by three types of traders, mainly foreign and retail traders, who are the most influential in trading values in the Thai stock market. Traders with the competence to dynamically adapt their order submission aggressiveness conditional to diverse market conditions are more likely to decrease their costs and gain more returns than their counterparts, as Harris (1998) proposed. Also, analysing the determinants of market conditions on which type of trader is willing to supply liquidity to the market by submitting limit orders and which type of trader is willing to demand liquidity from the market by placing market/marketable orders helps to understand how order-driven market functions (Bloomfield et al., 2005) like the Thai stock market and to gain insight into the process of price information (Ellul et al., 2007).

For all trades, transient price volatility has a negative relationship with the level of order aggressiveness on both the buying and selling sides, which is consistent with Foucault (1999), Handa et al. (2003), and Ranaldo (2004). High transient price volatility implies greater price fluctuations in the market, indicating uncertainty and potential risks. Traders may become less aggressive in submitting orders during periods of high volatility to mitigate potential losses and adverse price movement. The waiting time is referred to as the order submission process. If the order submission process is faster (slower), the incoming orders are less (more) aggressive (Ranaldo, 2004). The relative depth of the same and opposite sides influences the order submission aggressiveness of the incoming orders (Parlour, 1998; Handa et al., 2003), indicating consideration of the probability of execution by traders (Parlour, 1998). Traders may become more aggressive in submitting buying or selling orders if their side has a thicker market depth. In contrast, traders may become less aggressive in submitting buying or selling orders if their opposite side has a thicker market depth.

Various trader types in the Thai stock market employ unique trading submissions in response to different market conditions when considering their order submission aggressiveness. The results show evidence that foreign traders apply strategic trading submission, as reflected by their substantial order cancellations. The foreign traders account for 63.66% and 70.72% of total cancelling orders on the buying and selling sides, respectively. This noteworthy observation suggests that they are sensitive to non-execution costs, making them decide promptly to cancel their standing orders and resubmit them to ensure execution. There is further evidence regarding their sensitivity to non-execution risks by placing aggressive orders in response to lower market liquidity and performing a proactive role in jumping the order queue during periods of increased pending orders on their side of the market. However, a note of caution is observed in their approach, particularly in the context of avoiding picking off risks, as demonstrated by the tendency to temporarily distance themselves from the period of heightened volatility and submit passive orders.

On the other hand, during periods of heightened volatility in the market, institutional traders submit aggressive orders on the buying side to earn profit from "picking off" stale limit orders, consistent with the findings of Duong et al. (2009). However, they are risk averse and submit passive orders on the selling side when holding stocks in order to control the risk of picking off. Trading behaviours of institutional traders may suggest that they purchase stocks with information motives (Saar, 2001). However, when they sell, they are concerned about a higher transaction risk against informed traders who remain on the opposite side to them (Ranaldo, 2004). Retail traders are slower than their counterparts, and their order submission pose risks of non-execution and picking off on both the buying and selling sides.

The remainder of this chapter is organised as follows. Section 2.2 reviews the literature regarding (i) trading patterns and performance across various trader types, (ii) performance evaluation of aggressive and passive trades, (iii) aggressive and passive trading strategies and market factors, (iv) previous studies of trading behaviours and performance in the Stock Exchange of Thailand (SET), and (v) determinants of order aggressiveness. Section 2.3 gives information regarding the methodology: (i) definition of order aggressiveness and (ii) the order aggressiveness model. In section 2.4, the data collection will be outlined. Section 2.5 provides the results regarding the descriptive statistics and the main results. Finally, we conclude our study in section 2.6.

2.2 Literature Review

2.2.1 Trading Patterns and Performance Across Various Trader Types

Several studies investigate the trading patterns of different types of investor, namely foreigners, individuals, and institutes. Many report that foreign investors employ momentum trading strategies (also called positive feedback trading) by buying past winners and selling past losers (Choe et al., 1999; Grinblatt and Keloharju, 2000; Froot et al., 2001; Kamesaka et al., 2003; Lin and Swanson, 2003; Richard, 2005), especially in emerging markets (Richard, 2005). With foreign inflows, we can also predict a positive return on foreign investors' trades in the market, which receives the cash inflow (Froot et al., 2001). By contrast, individual investors are contrarians (Odean, 1998; Choe et al., 1999; Odean, 1999; Grinblatt and Keloharju, 2000; Jackson, 2003; Richard, 2005; Bae et al., 2008). They tend to sell their winning stocks but hold on to their losing stocks (Odean, 1998; Odean, 1999). Regarding institutional investors, two main trading patterns are found. Some studies find institutional investors to engage in momentum trading strategies (Lakonishok et al., 1992; Nofsinger and Sias, 1999; Griffin et al., 2003; Cai and Zheng, 2004). Other studies find that institutions follow contrarian trading strategies (Grinblatt and Keloharju, 2000; Karolyi, 2002; Kamesake et al., 2003).

Apart from variations in trading strategies, diverse types of traders display a range of performances in their trades. Foreign investors' trading extrapolates future returns of equity relatively well (Froot and Ramadorai, 2001) and generates superior investment performance (Grinblatt and Keloharju, 2000). One explanation offered by the literature is that foreign traders have good market timing (Kamesaka et al., 2003; Bae et al., 2006). Individual investors are typically found to have poorer trading performance (Barber et al., 2009; Phansatan et al., 2012) because they earn poor net returns when adjusted for trading costs (Baber and Odean, 2000) and have poorer market timing (Kamesaka et al., 2003). Kaniel et al. (2008) find a positive relationship between individual investors' net trades and future returns in the short horizon. This finding means that stock prices increase in the month when individuals buy, and decrease when they sell intensely. Other studies indicate that domestic investors are better traders because they earn higher profits than foreign investors (Brennan and Cao, 1997; Choe et al., 2005; Dvorak, 2005; Agarwal et al., 2009), because of the poor timing of foreigners' trades (Choe et al. (2005) or aggressive trading of foreign investors (Agrawal et al., 2009).

Institutional investors can be found to have advantages over individual investors in their use of information and trading cost advantages (Barber et al., 2009).

2.2.2 Performance Evaluation of Aggressive and Passive Trades

Barber et al. (2009) conduct an analysis of different investor types within the Taiwan Stock Exchange (TSE) by examining their trading strategies. The study reveals that the trading performance of various types of investor differs significantly based on the aggressiveness of their trading strategies. Specifically, individual investors incur trading losses, trading costs, and market-timing losses primarily due to aggressive orders rather than passive ones. In contrast, institutional investors exhibit profitability in both passive and aggressive trades, with a notable emphasis on gains derived from passive orders. Their passive trades provide liquidity to uninformed investors, often categorised as individual investors who engage in aggressive trading.

On a different note, Agrawal et al. (2009) focus on the performance of foreign and domestic investors in the Jakarta Stock Exchange (JSX). They classify executed orders into initiated and non-initiated orders on the buying and selling sides. They also identify the counterparties who submit two types of these executed orders. Initiated orders are those that initiate trades, like market/marketable orders. Non-initiated orders, like limit orders, are those executed by incoming initiated orders. Their findings indicate that, in general, foreign investors under-perform against domestic investors in their aggressive trading behaviour. Notably, the inferior performance of foreign investors is attributed primarily to their non-initiated orders. Conversely, their initiated orders outperform those of their domestic counterparts. Additionally, the study highlight the fact that foreign investors display higher levels of aggressiveness than their domestic counterparts.

2.2.3 Aggressive and Passive Trading Strategies and Market Factors

Chiu et al. (2017) provide conclusions concerning the distinguishing trading behaviours of traders in the Taiwan index futures market, underscoring that trader types show various trading patterns in order of aggressiveness and trading patience. Foreign institutional traders prefer to submit more limit orders rather than market orders. In contrast, individual traders focus their strategy on a more aggressive order submission. The complete limit order book information influences decisions on order placement among most traders. In particular, institutional traders will likely place more aggressive orders when the same-side depth is greater than the opposite-side depth. There is a positive association between order aggressiveness and order flow momentum among all trader types, demonstrating the persistence of order flow. Significantly, foreign institutional traders demonstrate a less pronounced response to changes in momentum shocks than individual traders. Moreover, traders react quickly to the changes in spreads, order size, and transitory volatility in adapting their order submission strategies. Different types of trader are adept at adjusting their aggressiveness level according to these factors, adopting a strategic approach to handling trading costs and satisfying liquidity needs.

In a related study, Park et al. (2019) provide insights into how foreigners' inflows impact the behavioural biases of domestic traders in the South Korean stock market. Their empirical study aims to support the hypothesis of "fear of the unfamiliar", which means that individual investors follow their inclination more on realised gains and sell stocks in their holdings that have experienced sustained recent increases in foreign investors' net purchases. Importantly, the expectation of future returns is not a reason for this behaviour. This study also emphasises that individual investors step back from trading stocks with a high degree of foreign ownership because they are reluctant to trade alongside unfamiliar groups of investors, namely foreigners. These findings suggest that the heightened behavioural biases of individual investors influence their trading behaviours when they observe foreign investors' entry into the market. These findings carry implications for investor protection and the long-term stability of equity markets in emerging economies.

In a similar vein, Duong et al. (2009) study the determinants of the order aggressiveness of institutional and individual investors in the Australian Stock Exchange (ASX), aiming to underscore its association with market depth on the same and opposite sides. Their findings demonstrate a positive relationship between order aggressiveness among individuals and institutions with same-side market depth, and a negative relationship between order aggressiveness among those with opposite-side market depth, indicating that traders consider the risk of non-execution when formulating their submission strategy. Broader spreads, particularly in trading in large-cap stocks, make individual and institutional traders likely to place less aggressive orders. However, individual investors trade more aggressively in mid-cap stocks, although a wider spread arises. These different trading behaviours of individual traders are attributed to their relative informational disadvantage when compared to their counterparts, like institutions. Institutional investors tend to trade more aggressively in volatile market conditions, strategically aiming to gain profit from stale limit orders with exposure to pick-off risk. Furthermore, they are more inclined to order aggressiveness on the selling side rather than the buying side, indicating that their clear perception of the opportunity cost of not selling outweighs that of not buying.

2.2.4 Previous Studies of Trading Behaviours and Performance in the Stock Exchange of Thailand (SET)

Some studies have investigated investors' trading behaviours and performance in the Stock Exchange of Thailand (SET). Phansatan et al. (2012) examine the trading patterns and trade performance of foreign, institutional, individual, and proprietary traders in the SET. They use weekly aggregated purchases and sales of the SET 50 data set over 6-year periods from January 1999 to December 2004. They find that foreign investors apply a positive feedback and momentum strategy, with foreign investors providing adept at short-term market timing. However, compared to domestic investors, foreign investors exhibit poor security selection performance, indicating a macro (market timing) but no micro (security selection) information advantage. Institutions and proprietary traders also display poor security selection trading performance. By contrast, individual investors follow herding behaviours and show fairly good security selection trading performance. Nevertheless, individual investors' gains in their security selection disappear due to market timing losses. Padungsaksawasdi (2020) studies aggregated herd behaviour without categorising types of investors in the SET. He examines the relationship between these aggregated herd behaviours and firm-specific information. He finds that firm-specific information plays a crucial role in herd behaviours, indicating that less corporate transparency, more noise trading, large asymmetric risk, and low liquidity are the main drivers of intentional herd behaviour.

However, none of these studies aims to delve into the trading aggressiveness of different types of investor in the Thai stock market. Also, no previous study examines the influence of market conditions on the trading aggressiveness of different types of investor in the Thai stock market.

2.2.5 Determinants of Order Aggressiveness

The level of order aggressiveness is significantly influenced by major determinants like the waiting time, the depth on the same side of the incoming order, the depth on the opposite side of the incoming order, the quoted spread, and transient return volatility (Ranaldo, 2004).

The waiting time is positively related to the level of order aggressiveness, meaning that the faster the order submission process is, the less aggressive the incoming orders will be (Ranaldo, 2004). Easley and O'Hara (1992) demonstrate that waiting time can affect prices, and non-trading periods are informative. Waiting time also has a positive relationship with spreads, implying that when waiting time increases, spreads will decrease. The subsequent trades provide more information than individual trades because trading intensity reflects events of uncertainty. They also suggest that the period of market inertia implies existing information. In contrast, the period of lively trade guides the directional flow of information. Studies by Admati and Pfleiderer (1988) and Harris (1994) support this positive relationship between quotation processes and order aggressiveness. Admati and Pfleiderer (1998) argue that discretionary liquidity traders time their trades at a time when their transaction costs can be minimised. Harris (1994) also supports the idea that market conditions regarding time priority and the discrete price grid provide benefits of fast movement and of competition between liquidity providers.

Regarding the depth of the same (opposite) side of the incoming order influencing the level of order aggressiveness, this is positively (negatively) related to order aggressiveness. This means that if there is thicker market depth on the buying (selling) side, the order aggressiveness of the incoming buyer (seller) will be stronger. Also, suppose market depth thickens on the buying (selling) side. In that case, the weaker order aggressiveness will be for the incoming seller (buyer). Parlour (1998) proposes that the optimal choice of traders would be to submit between limit and market order, which is critically dependent on the state of the limit order book. In her dynamic model of the limit order book market, the traders realise that their orders will affect the strategies of other traders who follow because of their trading purposes. The major determinants of the probability of execution are the size of the limit order book and traders' beliefs concerning the arrival of incoming order placement. More precisely, both sides of the limit order book are the major determinants of traders' order choices. As a result, when there is a thickness on the buying side of the order book, the incoming buying traders will place a market order. The selling traders also rationally predict that the thickness of the selling side of the order book reduces their probability of execution. Handa et al. (2003) also explain the thickness of the depth of the limit order book as a proxy of the fraction of high-value and low-value traders. The buying (selling) competition is generated by the greater fraction of high-value (low-value) traders, and this engenders a lower probability of execution, resulting in more attractive buying (selling) market orders. Ranaldo (2004) empirically investigates these hypotheses by indicating that there is a positive association between the level of order aggressiveness of the incoming buying (selling) traders and the thickness of the buying (selling) side of the order book. His findings confirm a positive association between the level of order aggressiveness of the incoming buying or selling traders and the depth of the queue on their side. His findings also confirm a negative relationship between the level of order aggressiveness of the incoming buying (selling) traders and the depth of the queue on the selling (buying) side.

The quoted spread and transient return volatility have inverse relationships with the level of order aggressiveness. This suggests that if the spread is wider, the order aggressiveness will weaken. Also, if there is higher volatility, the order aggressiveness will be weaker. Foucault (1999) conducts a game theoretic model pertaining to price formation and traders' choices of orders between limit and market orders in a dynamic limit order market. He implies that the lower (higher) level of order aggressiveness is caused by a wider (narrower) spread, or by a higher (lower) volatility, because traders need to seek more compensation for the picking-off risk when confronting higher volatility and wider spread. These findings are consistent with those of Handa et al. (2003), that changes in the fraction of high-value and low-value traders lead to changes in the size of the spread and the level of order aggressiveness in the opposite direction, and this, in turn, is expected to result in a narrower (wider) spread with a higher (lower) level of order aggressiveness. Ranaldo (2004) empirically tests these hypotheses by presuming that there is a positive association between transient return volatility as a proxy of volatility, the quoted spread as a proxy for the size of the spread, and the lower level of order aggressiveness. To avoid the problem of econometric issues like multicollinearity due to the high correlation between the size of spread and volatility, he carries out the ordered probit regression with transient return volatility as the sole explanatory variable separate from the others, including the size of the spread. His findings support those of Foucault (1999) and Handa et al. (2003) that the transient return volatility and the quoted spread are negatively related to the level of order aggressiveness.

2.3 Methodology

2.3.1 Definition of Order Aggressiveness

Traders demanding immediate order execution for liquidity purposes, or possessing superior information about the stock, opt for market orders, categorising them as impatient investors and liquidity demanders. On the opposite side, those who choose limit orders are considered patient investors and liquidity providers. This group faces a lower probability of execution, potential issues like stale limit orders, and the risk of being picked off (Ranaldo, 2004).

2.3.2 The Order Aggressiveness Model

This study follows the spirit of Hausman et al. (1992), Ranaldo (2004) and Chiu et al. (2017). It also employs the ordered logit model to analyse order aggressiveness, as used in Chiu et al. (2017). Therefore, this study conducts an ordered logit regression and an analysis of the marginal probabilities via the following equation.

$$y_{i,t}^{*j} = a^j + \sum_{m=1}^{5} b_m^j x_{i,m,t-1}^j + \delta_0^j D_{i,F}^j + \varphi_0^j D_{i,I}^j$$

$$+D_{i,F}^j\left(\sum_{m=1}^{5} \delta_m^j x_{i,m,t-1}^j\right)+D_{i,I}^j\left(\sum_{m=1}^{5} \varphi_m^j x_{i,m,t-1}^j\right) + \varepsilon_{i,t}^j \quad (2.1)$$

Where

$y_{i,t}^{*j}$ = the extent of order aggressiveness ranked by five order choices from the greatest to the least order aggressiveness for two trade directions (j = buy or sell) of order submission in stock i at time t,

a^j = an intercept of the model,

$x^j_{i,m,t-1}$ = the five explanatory variables (m = 1, …,5): (1) the depth on the same side of the incoming order (DSameVol), (2) the depth on the opposite side of the incoming order (DOppVol), (3) the quoted spread (Qspread), (4) the waiting time of order (Wtime), and (5) the price volatility (Pvolat) in stock i at time $t-1$,

$D^j_{i,F}$ = a dummy variable that equals unity for traders who are foreign and submit their orders in stock i at time t,

$D^j_{i,I}$ = a dummy variable that equals unity for traders who are institutional and submit their orders in stock i at time t,

$\varepsilon^j_{i,t}$ = the residual, which is independent but not identically distributed.

As mentioned in equation (2.1) above that $x^j_{i,m,t-1}$ stands for five independent variables (m) relating to the state of the limit order book, the definition of each variable can be explained in terms of the transaction time as follows. Firstly, the depth on the same side of the incoming order (DSameVol) is generated from the number of pending shares divided by 10,000 at the best bid (ask) as the orders arrive at time t. Secondly, the depth on the opposite side of the incoming order (DOppVol) represents the number of accumulated unexecuted shares divided by 10,000 on the opposite side of the best bid (ask) as the order is coming at time t. Next, the quoted spread (Qspread) is the difference between the best bid and the best ask price as the traders submit their orders at time t. The fourth variable is the waiting time of order (Wtime), which is proxied by the average of time elapsed, which is generated from the subsequence of order arrivals in the most recently continuous three orders (Sandas, 2001; Ranaldo, 2004). Finally, price volatility (Pvolat) is the transitory return volatility calculated from the standard deviation of the mid-quote returns between t-20 and t.[2]

In this analysis, we categorise the direction of orders into two sides: the buying and selling sides. Hence, the data will incorporate two subsamples of order flows: one for each stock's buying and selling sides. Each subsample consists of the five order types of aggressiveness, from the most aggressive to the least aggressive on each side of the order book at the time t: (1) a buy (sell) market/marketable order, (2) a buy (sell) limit order within the

[2] For more detailed information, see appendix B.

previous quotes, (3) a buy (sell) limit order at the previous quotes, (4) a buy (sell) limit order behind the previous quotes, and (5) the cancellation of existing buy (sell) limit orders.[3]

The following equation represents the state-space partition for each submission of each stock (i):

$$y^{j}_{r,t} = \begin{cases} 1 & \text{if} -\infty < y^{*j}_{t} \leq \tau^{j}_{1} \\ k & \text{if } \tau^{j}_{k-1} < y^{*j}_{t} \leq \tau^{j}_{k} \quad \text{for } k = 2,3,4, \\ 5 & \text{if } \tau^{j}_{4} < y^{*j}_{t} < \infty \end{cases} \tag{2.2}$$

where

$y^{j}_{r,t}$ = the discrete dependent variable indicating the order type $r = 1, \ldots, 5$,

τ^{j}_{k} = the logit thresholds with five different values from τ^{j}_{1} to τ^{j}_{5},

Regarding equations (2.1) and (2.2), the cumulative probabilities for each submission of each stock (i) are as follows:

$$\begin{aligned}
\Pr\left[y^{j}_{i,t} = 1\right] &= \Gamma\left(\hat{\tau}^{j}_{1} - E\left[x^{j}_{i,m,t}\right]\hat{b}^{j}_{m} - E\left[D^{j}_{i,F}\right]\hat{\delta}^{j}_{0} - E\left[D^{j}_{i,I}\right]\hat{\varphi}^{j}_{0} - E\left[D^{j}_{i,F}x^{j}_{i,m,t}\right]\hat{\delta}^{j}_{m} - \right. \\
&\qquad \left. E\left[D^{j}_{i,I}x^{j}_{i,m,t}\right]\hat{\varphi}^{j}_{m}\right), \\
\Pr\left[y^{j}_{i,t} = k\right] &= \Gamma\left(\hat{\tau}^{j}_{k} - E\left[x^{j}_{i,m,t}\right]\hat{b}^{j}_{m} - E\left[D^{j}_{i,F}\right]\hat{\delta}^{j}_{0} - E\left[D^{j}_{i,I}\right]\hat{\varphi}^{j}_{0} - E\left[D^{j}_{i,F}x^{j}_{i,m,t}\right]\hat{\delta}^{j}_{m} - \right. \\
&\qquad \left. E\left[D^{j}_{i,I}x^{j}_{i,m,t}\right]\hat{\varphi}^{j}_{m}\right) - \Gamma\left(\hat{\tau}^{j}_{k-1} - E\left[x^{j}_{i,m,t}\right]\hat{b}^{j}_{m} - E\left[D^{j}_{i,F}\right]\hat{\delta}^{j}_{0} - \right. \\
&\qquad \left. E\left[D^{j}_{i,I}\right]\hat{\varphi}^{j}_{0} - E\left[D^{j}_{i,F}x^{j}_{i,m,t}\right]\hat{\delta}^{j}_{m} - E\left[D^{j}_{i,I}x^{j}_{i,m,t}\right]\hat{\varphi}^{j}_{m}\right) \quad \text{for } k = 2,3,4, \\
\Pr\left[y^{j}_{i,t} = 5\right] &= 1 - \Gamma\left(\hat{\tau}^{j}_{4} - E\left[x^{j}_{i,m,t}\right]\hat{b}^{j}_{m} - E\left[D^{j}_{i,F}\right]\hat{\delta}^{j}_{0} - E\left[D^{j}_{i,I}\right]\hat{\varphi}^{j}_{0} - \right. \\
&\qquad \left. E\left[D^{j}_{i,F}x^{j}_{i,m,t}\right]\hat{\delta}^{j}_{m} - E\left[D^{j}_{i,I}x^{j}_{i,m,t}\right]\hat{\varphi}^{j}_{m}\right),
\end{aligned} \tag{2.3}$$

where $\Gamma(.)$ = the cumulative logit distribution.

[3] In Ranaldo (2004), there are five slightly different order types, as follows: (1) a large market order, (2) a small market order, (3) a limit order within the previous quotes, (4) a limit order at the previous quotes, and (5) a withdrawal of an existing order.

2.4 Collection, Analysis and Evaluation of Data

We collected trading data from the SET (Stock Exchange of Thailand) from July to December 2019. Since there are two trading sessions in the morning and afternoon in which market participants can trade within the SET, the data spans trading each day between 10:05 AM - 12:25 PM and 2:35 PM - 4:25 PM local time. The dataset includes detailed information such as the execution status of the order (whether it is executed or cancelled), timestamps, company codes, stock prices, trade volumes, and trade directions (buy or sell), all recorded on a tick-by-tick basis.

The sample observations comprise the 100 stocks that make up the SET100 Index. The SET100 is a combination of 2 groups of stocks. The first group consists of stocks in the SET50 index, the 50 largest and highest quality Thai blue-chip stocks, as determined by market capitalisation, free float, transparency regulations, and industries. The second group comprises a further 50 second-largest and second-highest quality Thai stocks. The SET 100 Index incorporates the 100 most actively traded stocks and the highest quality publicly traded Thai companies, and presents a broad cross-section of industries. However, the study removes stocks in the SET100 Index that are split or delisted during the observation period.

2.5 Results

2.5.1 Descriptive Statistics

Tables 2.1-2.4 report the descriptive statistics of order submissions on the buying and selling sides in five types of order aggressiveness,[4] quote spread (Qspread), two kinds of waiting time (WTime#1[5] and Wtime#2[6]), transient price volatility (Pvolat), the depth of the same side (DSameVol), the depth of the opposite side (DOppVol), the volumes, and the values, respectively. These tables give information in relation to the overall outlook and focus on three

[4] Types of order aggressiveness in both the buying and selling sides can be organised by the level of order aggressiveness, from the most passive to the most aggressive: the least aggressive (the most passive) in type 1 (cancellation) and the level is more aggressive in type 2 (bid/ask behind), type 3 (bid/ask at), type 4 (bid/ask within) respectively, and the most aggressive (the least passive) is order type 5 (marketable buy/sell).

[5] The values of average time elapsed between the last three orders, which is subsequently placed by traders from time t to $t - 3$ (Sandas, 2001; Ranaldo, 2004).

[6] The values of different time between time when traders placed their orders until being executed (for order types 2-5) or until being cancelled (for type 1).

types of trader: retail, foreign, and institutional, respectively. Also, the bold (italic) numbers shown on the selling side report greater (lesser) values than those on the buying side; thus, all values on the selling side differ from those on the buying side.

Five types of order aggressiveness in the overall view, and three groups of traders in terms of the number, volumes, and values of order submission, are also illustrated in Figures 2.1-2.3, respectively. Figures 2.1-2.3(a) and (b) illustrate the overall information on the buying and selling sides. Figures 2.1-2.3(c) and (d) depict the information of each type of trader (retail, foreign, and institutional), and Figures 2.1-2.3(e) and (f) portray the information in terms of a fraction among three types of trader.

The overall trend in the dataset reveals a higher number of submitted orders on the buying side (23,497,631) compared to the selling side (22,722,063). Retail traders display the same pattern, with 9,691,696 buy-side orders and 7,193,347 sell-side orders. However, foreign and institutional traders differ from this trend, displaying more sell-side orders than buy-side orders. Foreign traders show 11,489,849 sell-side orders versus 10,260,613 buy-side orders, while institutional traders display 4,038,867 sell-side orders compared to 3,545,322 buy-side orders.

Figures 2.1(a) and 2.1(b) illustrate the distribution of order submission for the buying and selling sides across five types of order aggressiveness. The largest fraction of order submissions falls under order type five (marketable buy/sell), constituting 44.68% on the buying side and 51.97% on the selling side. The statistics reveal that retail, foreign, and institutional traders predominantly place their orders as type five (marketable buy/sell). Retail traders represent 38.2%, foreign traders 46.14%, and institutional traders 57.94% on the marketable buying side, and 47.06%, 51.32%, and 62.58% on the marketable selling side, respectively.

The second largest proportion of order submissions from retail, institutional, and foreign traders differs. Retail and institutional traders place orders in type three (bid/ask at) as the second largest fraction. In contrast, the second largest proportion of the total number of orders submitted by foreign traders goes for type one (cancellation on both buying and selling sides), accounting for 63.66% and 70.72% of total cancelling orders on the buying and selling sides, respectively. In addtion, as seen in Figures 2.1(e) and 2.1(f), foreign traders have the number of placed orders with the largest fraction on both buying and selling sides compared to retail and institutional traders in all five types of order aggressiveness, except order type two (bid/ask behind) in which retail traders have the largest proportion of the number of submitted orders.

Regarding volume and value of orders in the five types of order aggressiveness, the most influential traders are foreigners. They account for 51.20% and 52.98% of the overall traded volume and 55.13% and 57.46% of all traded values on the buying and selling sides, respectively. Additionally, foreign traders display the highest volume and value of submitted orders on both buying and selling sides across all five types of order aggressiveness, except for order type two (bid/ask behind). Figures 2.2(e), 2.2(f), 2.3(e), and 2.3(f) show that retail traders take the lead in the volume and value of order placement in this specific order type.

Quoted spread and transient price volatility show a negative relationship with the level of order aggressiveness for the overall market and retail, foreign, and institutional traders.

Institutional investors have the shortest waiting time (#1) on the buying and selling sides for all types of order aggressiveness, compared to their counterparts. The order submission aggressiveness of institutions tends in this way to be anticipated by regularly splitting their order from parent orders to child orders. As noted by O'Hara (2015), Han and Kim (2020), and Kervel et al. (2023), the purpose of dividing their order with large numbers of shares into many smaller orders is to conceal their trade and avoid being detected by their counterparts.

Waiting time #2 is typically defined as how long the submitted order is executed in types two to five of order aggressiveness and how long the submitted order is cancelled in type one of order aggressiveness. Generally, the shortest transaction time for trading will be in type five of order aggressiveness (marketable buy/sell) since the submitted orders are suddenly executed. In contrast, the longest time of order submission for trading will be either type two (bid/ask behind) or type one (cancellation). Given the same technology for trading and the proximity to the stock market, how quickly the trader decides to trade is the main reason why some traders are faster trader than others. Thus, the evidence in Tables 2.1-2.4 implies that the faster traders are foreign traders (in Table 2.3) who trade in each type of order aggressiveness more quickly than the average (in Table 2.1) and than their counterparts (in Tables 2.2 and 2.4). In contrast, individual traders are slower traders compared to their counterparts. Also, when considering only the most passive order or order type one (cancellation), individual traders cancelled their pending orders more slowly compared to their counterparts, reflecting the fact that their orders tend to be stale and lead to the exposure of the risk of picking off.

Table 2.1: Statistics of Order Submissions: Overall

Buying Side	Order Type	Frequency	%	Qspread	Wtime#1	Wtime#2	Pvolat	DSameVol	DOppVol	Volumes (hundred)	%	Values (hundred Baht)	%
Order Aggressive													
Marketable Buy	5	10,499,515	44.68	0.233	1,819.93	1,261.46	0.973	1,889.54	1,914.76	96,491,493.70	30.56	2,106,689,789.241	31.06
Bid Within	4	115,449	0.49	0.500	1,375.92	6,274.27	5.418	1,915.47	1,417.83	1,031,477.10	0.33	24,871,481.298	0.37
Bid At	3	5,792,331	24.65	0.225	2,039.74	6,413.00	1.075	1,858.15	1,653.33	50,944,544.60	16.13	1,038,574,690.313	15.31
Bid Behind	2	1,370,967	5.83	0.245	2,073.15	20,407.69	1.085	1,631.74	1,459.37	8,562,071.80	2.71	199,791,571.738	2.95
Cancellation	1	5,719,369	24.34	0.249	3,165.13	6,358.54	1.200	1,482.87	1,542.36	158,718,582.30	50.27	3,412,281,801.359	50.31
			Average	0.237	2,214.13	4,913.70	1.082	1,767.90	1,730.66				
			Total							315,748,169.50		6,782,209,333.949	
Number of observations													23,497,631

Selling Side	Order Type	Frequency	%	Qspread	Wtime#1	Wtime#2	Pvolat	DSameVol	DOppVol	Volumes (hundred)	%	Values (hundred Baht)	%
Order Aggressive													
Marketable Sell	5	**11,809,219**	**51.97**	*0.229*	*1,555.03*	**1,696.80**	*0.905*	*1,873.70*	*1,786.40*	**105,648,224.80**	**37.52**	**2,178,844,269.055**	**35.69**
Ask Within	4	*102,752*	*0.45*	**0.507**	*1,300.20*	*5,872.82*	**5.597**	*1,576.20*	*1,334.58*	*709,756.00*	*0.25*	*20,085,372.895*	*0.33*
Ask At	3	*5,012,324*	*22.06*	**0.233**	*1,678.60*	*5,796.25*	**1.095**	*1,694.60*	*1,589.54*	*46,198,211.50*	**16.41**	*1,022,846,426.384*	**16.76**
Ask Behind	2	*927,408*	*4.08*	**0.248**	*1,944.43*	*19,377.23*	**1.212**	**1,826.07**	**1,500.74**	*7,454,939.10*	*2.65*	*185,478,564.687*	**3.04**
Cancellation	1	*4,870,360*	*21.43*	*0.248*	**3,256.82**	*6,093.42*	*1.165*	*1,469.51*	*1,504.87*	*121,538,701.00*	*43.17*	*2,696,584,739.391*	*44.18*
			Average	*0.236*	*1,961.80*	*4,284.02*	*1.036*	*1,744.27*	*1,668.93*				
			Total							*281,549,832.40*		*6,103,839,372.412*	
Number of observations													*22,722,063*

Table 2.2: Statistics of Order Submissions: Retail Traders

Buying Side	Order Type	Frequency	%	Qspread	Wtime#1	Wtime#2	Pvolat	DSameVol	DOppVol	Volumes (hundred)	%	Values (hundred Baht)	%
Order Aggressive													
Marketable Buy	5	3,710,982	38.29	0.187	2,041.90	1,230.42	1.182	2,076.79	2,149.36	32,407,900.50	31.90	541,690,370.763	31.78
Bid Within	4	43,698	0.45	0.417	1,849.88	7,454.83	5.065	1,982.33	1,614.26	323,483.90	0.32	6,301,779.433	0.37
Bid At	3	3,158,068	32.59	0.200	2,465.67	8,183.64	1.124	1,838.42	1,822.77	22,574,934.60	22.22	361,640,855.361	21.22
Bid Behind	2	1,134,459	11.71	0.237	2,189.24	21,709.58	1.089	1,626.91	1,496.43	5,770,494.70	5.68	120,225,867.750	7.05
Cancellation	1	1,644,489	16.97	0.210	3,145.84	15,312.84	1.454	1,752.77	1,961.47	40,511,453.40	39.88	674,434,221.519	39.57
			Average	0.202	2,383.69	8,310.90	1.216	1,891.05	1,932.22				
			Total							101,588,267.10	32.17	1,704,293,094.826	25.13
Number of observations													9,691,696
Selling Side	**Order Type**	**Frequency**	**%**	**Qspread**	**Wtime#1**	**Wtime#2**	**Pvolat**	**DSameVol**	**DOppVol**	**Volumes (hundred)**	**%**	**Values (hundred Baht)**	**%**
Order Aggressive													
Marketable Sell	5	*3,384,961*	**47.06**	*0.179*	*1,853.09*	**2,212.12**	**1.277**	**2,100.79**	*2,124.07*	**35,469,292.70**	**44.08**	*533,467,289.677*	**40.03**
Ask Within	4	*29,694*	*0.41*	*0.385*	*1,597.21*	*7,346.27*	**5.636**	*1,748.37*	*1,561.12*	*205,884.80*	*0.25*	*4,236,679.578*	*0.32*
Ask At	3	*2,049,726*	*28.49*	*0.198*	*2,125.96*	*7,936.50*	**1.179**	*1,729.14*	**1,859.87**	*18,338,716.50*	**22.79**	*312,336,063.693*	**23.44**
Ask Behind	2	*711,468*	*9.89*	*0.234*	*2,131.63*	*21,463.77*	**1.251**	**1,857.71**	**1,593.19**	*4,860,171.40*	**6.04**	*108,827,643.537*	**8.17**
Cancellation	1	*1,017,498*	*14.14*	**0.211**	**3,245.75**	**17,080.18**	**1.491**	**1,771.91**	*1,953.05*	*21,595,323.40*	*26.84*	*373,642,292.166*	*28.04*
			Average	*0.195*	*2,154.33*	*7,871.66*	**1.295**	**1,922.87**	**1,969.76**				
			Total							*80,469,388.80*	*28.58*	*1,332,509,968.651*	*21.83*
Number of observations													*7,193,347*

Table 2.3: Statistics of Order Submissions: Foreign Traders

Buying Side	Order Type	Frequency	%	Qspread	Wtime#1	Wtime#2	Pvolat	DSameVol	DOppVol	Volumes (hundred)	%	Values (hundred Baht)	%
Order Aggressive													
Marketable Buy	5	4,734,214	46.14	0.260	2,071.70	866.95	0.804	1,804.35	1,718.64	39,733,763.10	24.58	964,739,211.371	25.80
Bid Within	4	47,155	0.46	0.560	1,304.83	4,037.01	5.992	1,887.88	1,373.31	449,065.30	0.28	11,118,134.853	0.30
Bid At	3	1,707,249	16.64	0.261	1,874.88	3,102.38	1.087	1,874.62	1,477.12	17,204,264.30	10.64	405,634,820.342	10.85
Bid Behind	2	131,205	1.28	0.286	1,997.93	9,374.52	0.955	1,626.47	1,295.57	1,246,108.40	0.77	34,226,553.434	0.91
Cancellation	1	3,640,790	35.48	0.264	3,276.96	2,175.67	1.091	1,380.27	1,372.85	103,011,143.20	63.73	2,323,375,463.674	62.14
			Average	0.263	2,462.15	1,826.63	0.978	1,663.68	1,548.76				
			Total							161,644,344.30	51.20	3,739,094,183.674	55.13
Number of observations													10,260,613

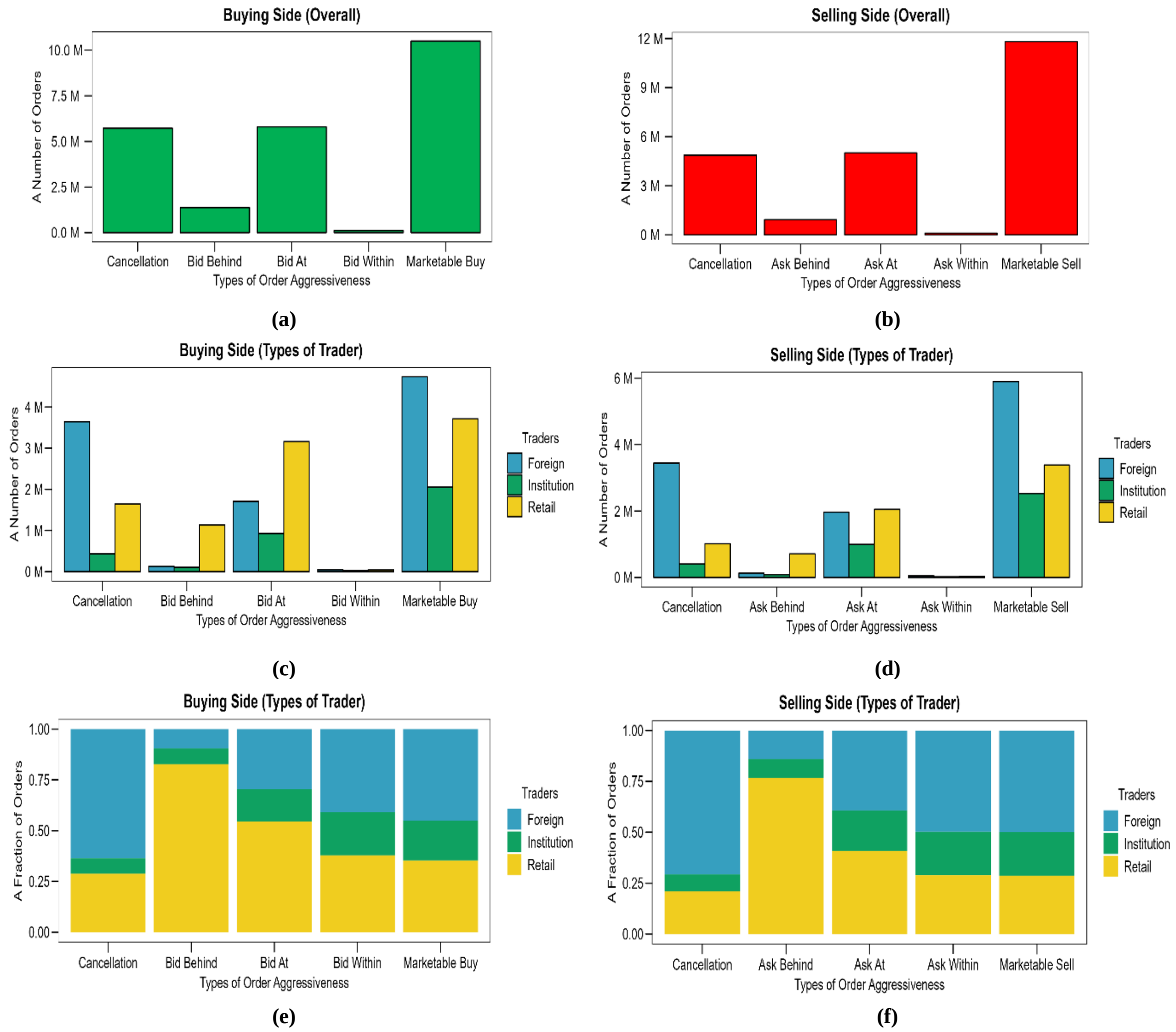
Selling Side	Order Type	Frequency	%	Qspread	Wtime#1	Wtime#2	Pvolat	DSameVol	DOppVol	Volumes (hundred)	%	Values (hundred Baht)	%
Order Aggressive													
Marketable Sell	5	**5,896,744**	**51.32**	*0.255*	*1,754.82*	**1,069.26**	*0.702*	**1,810.13**	*1,614.92*	**44,302,665.50**	**29.70**	***1,052,979,372.839***	***30.02***
Ask Within	4	**51,130**	*0.45*	*0.552*	**1,355.97**	*3,958.17*	*5.946*	*1,437.16*	*1,186.26*	*339,049.30*	*0.23*	*10,521,868.730*	0.30
Ask At	3	**1,966,755**	**17.12**	*0.260*	*1,662.92*	**3,343.48**	**1.129**	*1,639.28*	*1,428.94*	**17,328,641.40**	**11.62**	**441,845,875.811**	**12.60**
Ask Behind	2	*131,009*	*1.14*	**0.293**	*1,683.28*	*9,126.99*	**0.995**	*1,605.82*	**1,162.74**	**1,389,043.10**	**0.93**	**38,403,455.704**	**1.09**
Cancellation	1	*3,444,211*	*29.98*	*0.257*	**3,397.66**	**2,521.74**	*1.071*	**1,399.74**	**1,387.47**	*85,816,880.60*	*57.53*	*1,963,741,801.256*	*55.99*
			Average	*0.258*	*2,228.96*	**1,998.67**	*0.913*	*1,653.88*	*1,507.84*				
			Total							*149,176,279.90*	**52.98**	*3,507,492,374.340*	**57.46**
Number of observations													**11,489.849**

Table 2.4: Statistics of Order Submissions: Institutional Traders

Buying Side	Order Type	Frequency	%	Qspread	Wtime#1	Wtime#2	Pvolat	DSameVol	DOppVol	Volumes (hundred)	%	Values (hundred Baht)	%
Order Aggressive													
Marketable Buy	5	2,054,319	57.94	0.252	838.74	2,226.72	0.985	1,747.58	1,942.96	24,349,830.10	46.37	600,260,207.107	44.83
Bid Within	4	24,596	0.69	0.532	670.15	8,466.06	4.943	1,849.60	1,154.20	258,927.90	0.49	7,451,567.012	0.56
Bid At	3	927,014	26.15	0.246	892.33	6,478.00	0.886	1,895.03	1,400.62	11,165,345.70	21.26	271,299,014.610	20.26
Bid Behind	2	105,303	2.97	0.284	916.14	20,129.14	1.199	1,690.36	1,264.14	1,545,468.70	2.94	45,339,150.554	3.39
Cancellation	1	434,090	12.24	0.267	2,300.30	7,518.88	1.160	1,320.86	1,376.28	15,195,985.70	28.94	414,472,116.166	30.96
			Average	0.255	1,032.83	4,561.32	1.015	1,732.90	1,706.13				
			Total							52,515,558.10	16.63	1,338,822,055.449	19.74
Number of observations													3,545,322

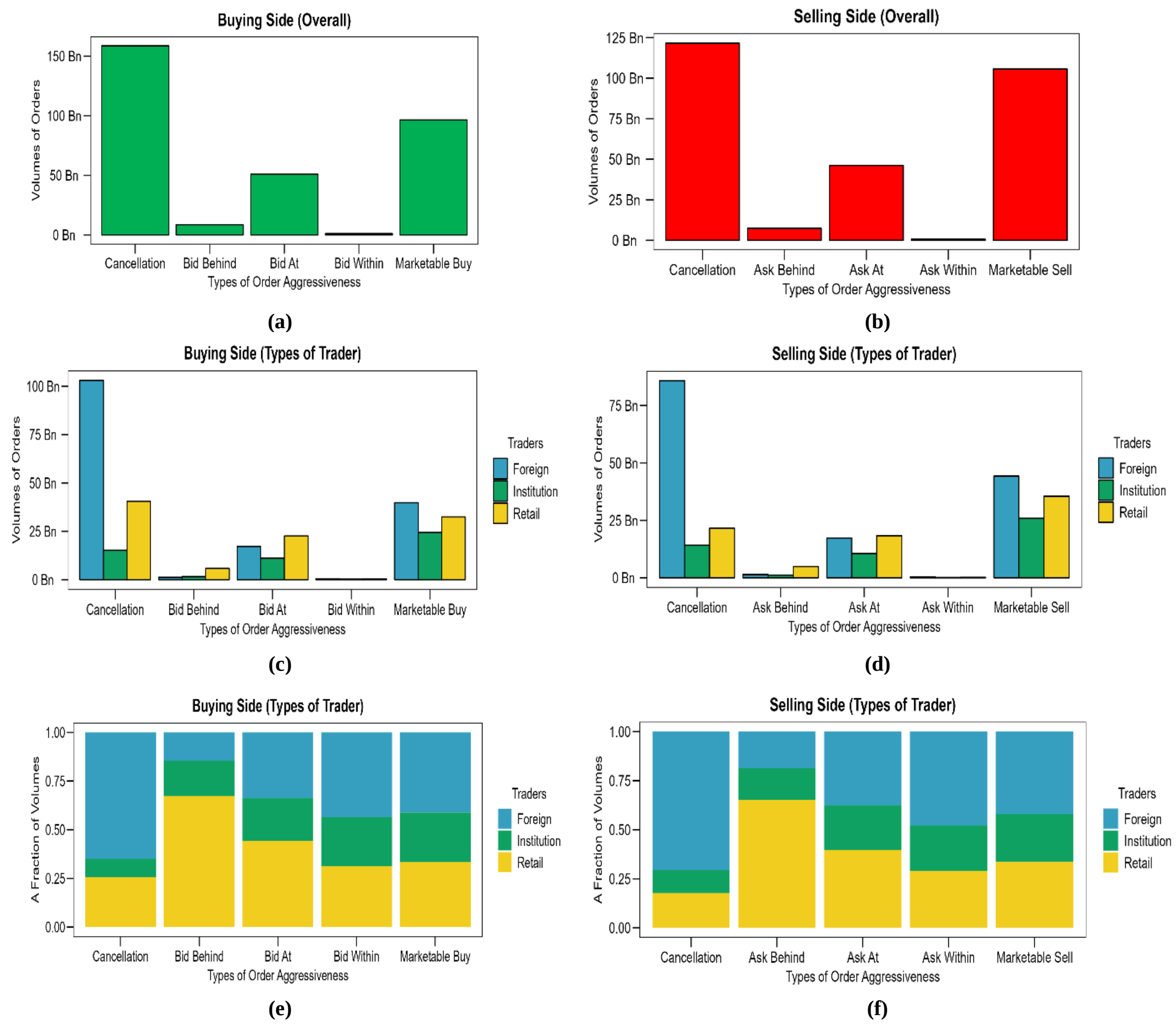
Selling Side	Order Type	Frequency	%	Qspread	Wtime#1	Wtime#2	Pvolat	DSameVol	DOppVol	Volumes (hundred)	%	Values (hundred Baht)	%
Order Aggressive													
Marketable Sell	5	**2,527,514**	**62.58**	*0.236*	*689.74*	**2,470.70**	*0.881*	*1,717.86*	*1,734.24*	**25,876,266.60**	**49.85**	*592,397,606.539*	**46.87**
Ask Within	4	*21,928*	*0.54*	**0.567**	**767.95**	*8,341.96*	*4.732*	*1,667.29*	**1,373.66**	*164,821.90*	*0.32*	*5,326,824.587*	*0.42*
Ask At	3	**995,843**	*24.66*	**0.250**	*788.73*	*6,235.16*	*0.856*	*1,732.78*	*1,350.29*	*10,530,853.60*	*20.29*	*268,664,486.880*	**21.26**
Ask Behind	2	*84,931*	*2.10*	**0.293**	*779.11*	*17,709.63*	**1.216**	**1,900.84**	*1,247.68*	*1,205,724.60*	*2.32*	*38,247,465.446*	*3.03*
Cancellation	1	*408,651*	*10.12*	**0.269**	*2,097.39*	**8,840.58**	*1.140*	*1,304.60*	**1,378.46**	*14,126,497.00*	*27.22*	*359,200,645.969*	*28.42*
			Average	*0.246*	*858.88*	*4,395.71*	*0.929*	*1,683.29*	*1,591.39*				
			Total							*51,904,163.70*	**18.44**	*1,263,837,029.421*	**20.71**
Number of observations													**4,038,867**

Figure 2.1: The Number of Orders in Five Types of Order Aggressiveness



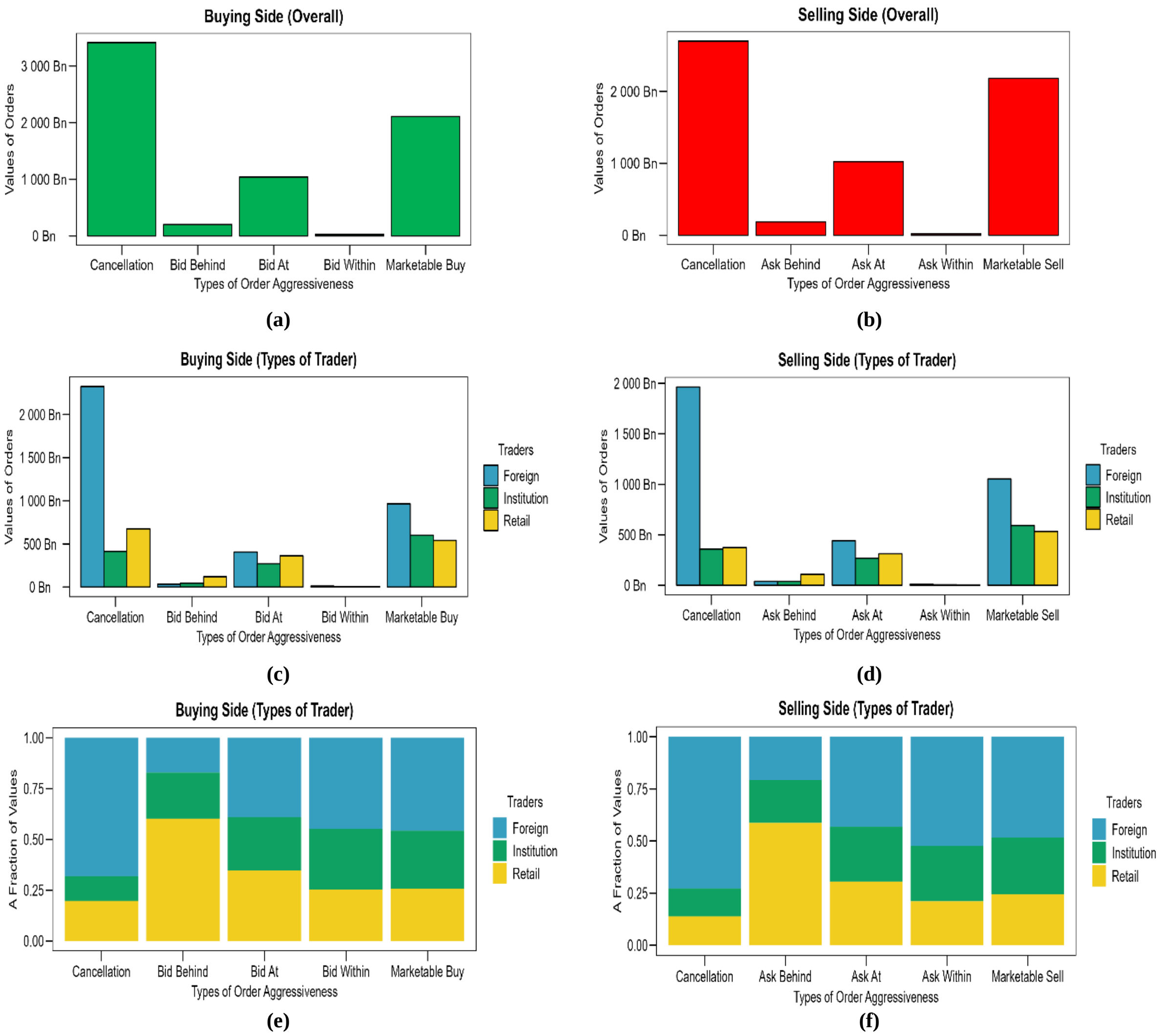
Notes: This figure reports the number of orders in five types of order aggressiveness. This figure also reports in six sub-figures illustrating (a) the overall number of orders on the buying side, (b) the overall number of orders on the selling side, (c) the number of orders in five types of order aggressiveness categorised by types of trader on the buying side, (d) the number of orders in five types of order aggressiveness categorised by types of trader on the selling side, (e) a fraction of orders in five types of order aggressiveness categorised by types of trader on the buying side, and (f) a fraction of orders in five types of order aggressiveness categorised by types of trader on the selling side.

Figure 2.2: The Volumes of Orders in Five Types of Order Aggressiveness



Notes: This figure reports the volumes of orders in five types of order aggressiveness. This figure also reports in six sub-figures illustrating (a) the overall volumes of orders on the buying side, (b) the overall volumes of orders on the selling side, (c) the volumes of orders in five types of order aggressiveness categorised by types of trader on the buying side, (d) the volumes of orders in five types of order aggressiveness categorised by types of trader on the selling side, (e) a fraction of volumes in five types of order aggressiveness categorised by types of trader on the buying side, and (f) a fraction of volumes in five types of order aggressiveness categorised by types of trader on the selling side.

Figure 2.3: The Values of Orders in Five Types of Order Aggressiveness



Notes: This figure reports the values of orders in five types of order aggressiveness. This figure also reports in six sub-figures illustrating (a) the overall values of orders on the buying side, (b) the overall values of orders on the selling side, (c) the values of orders in five types of order aggressiveness categorised by types of trader on the buying side, (d) the values of orders in five types of order aggressiveness categorised by types of trader on the selling side, (e) a fraction of values in five types of order aggressiveness categorised by types of trader on the buying side, and (f) a fraction of values in five types of order aggressiveness categorised by types of trader on the selling side.

2.5.2 Ordered Logit Regression and Marginal Effects

Tables 2.5 and 2.6 report the estimated coefficients of ordered logit regression analysis on the buying and selling sides of equation 2.1. Tables 2.7 and 2.8 show the marginal effects of the estimated ordered logit regression from Tables 2.5 and 2.6, respectively.

The quote spread (Qspread), the waiting time (Wtime), and the price volatility (Pvolat) are statistically significant and negative. The coefficients are -0.2836, -0.1785, and -30.5472 for the buying side and -0.4981, -0.2307, and -20.1410 for the selling side. These findings could indicate negative associations between the level of order aggressiveness and Qspread, Wtime, and Pvolat on both the buying and selling sides. These findings are consistent with those of Foucault (1999), Handa et al. (2003), and Ranaldo (2004), except for the waiting time, which is not consistent with the findings of Easley and O'Hara (1992), Harris (1994), Admati and Pfleiderer (1998), and Ranaldo (2004). These results suggest that as transient price volatility increases, traders become hesitant to place marketable orders and are more inclined to submit passive limit orders (Ranaldo, 2004). The reason supporting such instances is that limit order traders try to find more compensation for the risk of picking off, and marketable orders may become more costly if traders employ them (Foucault, 1999). Therefore, traders will submit more limit orders than marketable ones when market uncertainty increases. Also, passive orders will be submitted more frequently if there is a wider spread (Ranaldo, 2004). These findings are consistent with Hollifield et al. (2002), who indicate that successive marketable orders are less likely to occur when the spread widens. However, our results suggest that more aggressive orders are related to faster order submissions when considering the waiting time. These findings are inconsistent with those of Easley and O'Hara (1992), who propose that the process of order submission is slower when there is the submission of aggressive orders. This inconsistency may be because the order continuation might not directly relate to order aggressiveness. As Biais et al. (1995) and Hamao and Hasbrouck (1995) suggest, order persistence or order continuation might depend on information motives.

In contrast, the statistical analysis indicates that the depth of the same side (DSameVol) and the opposite side (DOppVol) are both significantly and positively correlated with the level of aggressiveness on both the buying and selling sides. Specifically, for the buying side, the coefficients are 0.2066 for DSameVol and 0.2200 for DOppVol, while for the selling side, the coefficients are 0.2006 for DSameVol and 0.1151 for DOppVol. These findings are consistent with prior research by Parlour (1998), Handa et al. (2003), and Ranaldo (2004). Notably, the higher coefficient of DSameVol (DOppVol) on the selling (buying) side in comparison to

DOppVol (DSameVOl) indicates that buyers are more concerned about DOppVol than DSameVol, while sellers prioritise their side over the opposite side. The results suggest that buyers adjust their order submissions in tandem with the available liquidity supply, a factor that holds greater significance than their considerations in relation to selling, as proposed by Ranaldo (2004).

There are different coefficient values between the buying and selling sides in Tables 2.5 and 2.6, respectively. Therefore, the conclusion might be drawn from these pieces of evidence that there is an asymmetry between order submission of buyers and sellers, which is consistent with the assumption of the model proposed by Saar (2001) and the findings of Ranaldo (2004), which are against the assumption of symmetry between the buying and selling sides.[7]

Regarding the dummy for foreign traders (D_F) and for institutional traders (D_I), the study uses retail traders as a reference group (base group) for comparison. As seen in Tables 2.5 and 2.6, holding other factors fixed, there are statistically negative coefficients for D_F on both the buying and selling sides, with -0.1687 and -0.2016, respectively, and there are statistically positive for D_I on both the buying and selling sides, with 0.6146 and 0.5386 respectively. These findings suggest that foreign traders are less aggressive (more passive) than retail traders. In contrast, institutional traders are more aggressive (less passive) than retail traders.

These findings indicate that institutional traders would be more aggressive than their counterparts because they may pursue informational advantage, as Barber et al. (2009) suggest. By contrast, foreigners are less aggressive (more passive) than their counterparts because they perform better when they appear to follow good market timing (Grinblatt and Keloharju, 2000; Kamesaka et al., 2003; Bae et al., 2006). This presumption of foreign trading decisions would be consistent with the findings in Table 2.3 that the largest and second-largest proportions of order aggressiveness relate to the marketable orders and cancellation orders, respectively, which are the apparent differences between the most aggressive and most passive trading strategies. Also, foreign traders' cancelled orders account for 63.66% and 70.72% of total cancelled orders on the buying and selling sides, respectively. When these traders observe good market timing, they may cancel limit orders and resubmit markable orders to jump the queue.

Regarding the interaction terms/effects section on both the buying and selling sides, when holding other factors fixed, the study also uses retail traders as a reference group (base group) for comparison. Foreigners are more aggressive than retail traders if there is an increase in

[7] Ranaldo assumes that if the estimation of the ordered probit regression on both buying and selling side generates similar values of coefficients, a symmetry between buyers and sellers will be held, but his findings show evidence of the rejection of this assumption and thereby a symmetry between the buying and the selling side is not held.

Qspread, at 0.2847 and 0.4965 on the buying and selling sides, respectively. Foreigners are also more aggressive than retail traders if there is an increase in DSameVol and DOppVol, at 0.4843 and 0.5778 on the buying and selling side for DSameVol, respectively at 0.5787 and 0.3317 on the buying and selling side for DOppVol, respectively. These findings demonstrate that foreign traders exhibit the most sensitivity to non-execution costs, reacting by submitting aggressive orders when the bid-ask spread increases and the market experiences reduced liquidity. When the market depth on their side thickens, they submit more aggressive orders by jumping the queue on their side close to the market to benefit from a higher probability of executing. They also follow more aggressive placement decisions when the market depth on the opposite side increases, implying that their trading submission decisions outweigh the non-execution risk on their side more than the opposite side.

By contrast, foreign traders are less aggressive (more passive) than retail traders if there is an increase in Wtime and Pvolat on both the buying and selling sides, at -0.1781 and -99.2710 on the buying side, respectively, and at -0.2541 and -158.4013 on the selling side, respectively. These findings suggest that they are less sensitive to the increased waiting time than retail traders, meaning they can wait longer for good market timing to obtain better performance. Regarding Pvolat, foreigners will reduce their risk exposure to picking-off by trading more passive orders farther from the market. These distant-order placement strategies will be beneficial if prices move far away from fundamental values (Harris, 1998). As seen in Tables 2.7 and 2.8, foreigners reduce their marketable orders by 245.10% on the buying side and by 395.07% on the selling side. Simultaneously, there is an increase in cancellation orders by 181.62% on the buying side and by 264.69% on the selling side. Trading behaviours of foreigners in the Thai stock market illustrate sensibly and adaptably dynamic trading decisions to maximise their profit and minimise their loss by being risk averse and avoiding the risk of picking off arising in the market, combined with pursuing the market timing strategies. It is worth noting that, overall, foreigners act as more passive traders than their counterparts. However, they demonstrate more aggressive trading according to all market factors except Wtime and Pvolat, suggesting that these factors, Pvolat in particular, are the most influential market factors in encouraging increased passivity.

As discussed in Section 2.5.1 regarding Waiting time #2 in Table 2.3, foreign traders are faster than their counterparts. Notably, foreign traders are twice as fast as retail and institutional traders in type five of order aggressiveness (marketable buying/selling) on both the buying and selling sides. In type one of order aggressiveness (cancellation on both buying and selling sides), foreign traders are four times as fast as institutional traders and eight times as fast as retail traders. Such instances may imply that foreign traders are more sensitive to current market conditions than retail and institutional traders in search of good market timing.

The presumption that foreign traders are much faster than retail and institutional traders in the Thai stock market should have supporting evidence. A possible example is that foreign traders use high-frequency trading (HFT) to act as fast traders. As noted by several papers, foreign traders probably use a style of order execution lying between aggression and passivity or between one large-volume order and split smaller orders (Benos and Sagade, 2016),[8] a form of manipulation like quote stuffing,[9] or arbitrage and directional strategies (Aldridge, 2013), or to stay in front of the queue (Manahov, 2021), which might be closely related to the large number of cancelled orders by foreigners who resubmit their orders based on the most recent market conditions. These results may also be consistent with the report of the SET in 2023. According to this report (SET, 2023d), the proportion of the HFTs and non-HFTs of foreign investors in the SET is 11% and 23%, respectively. Around 87% and 81% of program trading is traded by foreign HFTs and non-HFTs in stocks listed in the SET100 index.

Institutional traders are more aggressive than their counterparts if there is an increase in Pvolat on the buying side, at 2.2847. However, they are more passive than retail traders when considering an increase in Pvolat on the selling side, at -41.9743. Institutions are more aggressive than retail traders if there is an increase in Qspread, at 0.2099 and 0.2083 on the buying and selling sides, respectively. Also, institutions are more aggressive than their counterparts if the DOppVol increases, at 1.2535 and 0.7729 on the buying and selling side, respectively. However, they are more passive than their counterparts when the DSameVol increases, at -0.1750 and -0.1466 on the buying and the selling sides, respectively. These findings indicate that institutional traders tend to place more aggressive buying orders in volatile market conditions, strategically aiming to profit from "picking off" stale limit orders, which is consistent with the findings of Duong et al. (2009). However, when holding stocks, they are risk averse, placing more passive orders on the selling side due to increased market volatility. They place more aggressive orders when the market depth on the opposite side thickens. However, they revert to passive orders when there is an increase in the market depth on the same side. These findings suggest that the risk of non-execution is a concern for institutions when considering the changes in the bid-ask spread rather than the market depth.

[8] Their findings conclude that HFTs applying aggressive orders are informed, whereas HFTs deploying passive orders are market makers.

[9] Quote Stuffing is viewed as manipulating financial markets by letting HFTs send and cancel their enormous orders in an attempt to create uncertainty for other traders, consume all bandwidth and thereby prevent or slowdown the order submission process of other traders (See Easley et al., 2012; The U.K. Government Office for Science, 2012; Narang, 2013).

Retail traders are at risk of picking off when considering the Pvolat. The coefficient of institutions is greater than that of retail traders. The coefficient of foreigners is less than that of retail traders, indicating that retail traders get exposure by picking off risk to institutional traders on the buying side. In contrast, on the selling side, institutional and foreign traders are more passive than retail traders, as shown by the coefficients of institutions and foreigners, which are negative and less than that of retail traders, suggesting that when holding stocks, retail traders are less concerned about the heightened market volatility than their counterparts, and incur risks of picking-off. As discussed in Section 2.5.1 regarding Waiting time #2 in Table 2.2 compared to Tables 2.3 and 2.4, retail traders are slower traders than their counterparts, demonstrating that they are more likely to incur stale prices, stale limit orders, and a higher probability of non-execution, meaning that they are at risk of picking off by traders who engage good market time strategies from informational advantage at a faster pace, like foreign traders.

Suppose the Thai stock market experiences a capital inflow of foreigners, who have the most strategic trading approach and are the most influential traders, reflected by the highest fraction of traded values, at 55.13% and 57.46% of all traded values in the Thai stock market, as shown in Table 2.3. This scenario may have the most adverse effect on the trading performance of their counterparts, especially individual traders who are exposed to risks of picking off and non-execution, and trade slower than foreigners.

Although this study does not provide the results regarding the optimality of trading strategies, we may infer from this study by linking to the literature regarding the optimality of trading strategies, as discussed in Nofsinger and Sias (1999), Cohen et al. (2002), Kamesaka et al. (2003), Barber et al. (2009) and Daniel and Hirshleifer (2015) as follows. We could imply that the submission strategies of all traders who employ marketable orders to be executed may not guarantee superior performance in the SET. Barber et al. (2009) suggest that trading cost and market-timing losses occur when retail traders employ aggressive rather than passive trading. Their aggressive orders may reflect herding behaviours by responding to masses or sentiments (Nofsinger and Sias, 1999) without information advantage. As suggested by Kamesaka et al. (2003), retail traders are often overconfident, and this causes poor investment performance. Overestimation and overconfidence tend to result in more frequent trading (Graham et al., 2005; Glaser and Weber, 2007; Grinblatt and Keloharju, 2009), as reflected in retail traders' aggression (Daniel and Hirshleifer, 2015). In contrast to retail traders, institutional traders can profit from their aggressiveness in trading. When motivated by informational advantage, institutional traders will engage in aggressive trading (Barber et al., 2009). In the case of passive trading, institutions that underreact to stock prices apply passive trading to trade against retail traders who engage in aggressive trading and overreact in response to good news (Cohen et al., 2002). Foreigners also profit from trading, accounting for nearly half of the profit institutional traders earn. Suppose this arises in relation to retail traders in the SET. In that case, we can assume that retail traders are disadvantaged when they trade against professionals (Barber et al., 2009).

To sum up, foreign traders are the most strategic traders implementing order submission aggressiveness in the Thai stock market, as supported by their substantial number of cancelled orders. Their order submission aggressiveness indicates that they are sensitive to the risk of non-execution, adeptly adjusting their pending orders to be cancelled and then resubmitting orders to ensure execution. Increased bid-ask spread and reduced market liquidity are other crucial factors that make foreigners sensitive to non-execution costs, responding by submitting aggressive orders. They adjust their order submission aggressiveness to greater passivity when fewer orders are submitted, indicating reduced competitiveness. Conversely, they adapt their order submission aggressiveness to be more aggressive when the market depth from their side thickens, strategically ensuring that their orders will be executed by cutting in line. However, their order submission aggressiveness are observed as a note of caution, especially in alleviating picking-off risks caused by high volatility. Foreigners are also considered faster traders than their counterparts. Institutional traders adjust their order submission aggressiveness depending on market volatility in particular. When there is heightened market volatility on the buying side, they see profit opportunities by trading more aggressively from picking off stale limit orders on the buying side from retail traders. However, on the selling side, they step back and place less aggressive orders. In contrast to foreigners, retail traders are slower, and their order submission aggressiveness is exposed to non-execution and picking off risks to their counterparts.

Table 2.5: Ordered Logit Regressions: Buying Side

Independent Variables	Coefficient	Odds Ratio	Std. Error	t-Stat	Confidence Interval 2.5%	Confidence Interval 97.5%
Quote Spread (Qspread)	-0.2836***	0.7531	0.00231	-122.8087	0.7497	0.7565
Waiting Time (Wtime)	-0.1785***	0.8366	0.00331	-53.8583	0.8312	0.8420
Price Volatility (Pvolat)	-30.5472***	5.4142×10^{-14}	0.83856	-36.4280	1.0465×10^{-14}	2.8011×10^{-13}
Depth of the Same Side (DSameVol)	0.2066***	1.2295	0.00684	30.2177	1.2132	1.2461
Depth of the Opposite Side (DOppVol)	0.2200***	1.2461	0.00735	29.9449	1.2283	1.2642
d_R (Dummy for Retail Traders; Reference Group)		1.0000				
d_F (Dummy for Foreign Traders)	-0.1687***	0.8447	0.00119	-141.6652	0.8428	0.8467
d_I (Dummy for Institutional Traders)	0.6146***	1.8488	0.00175	351.7637	1.8425	1.8552
Interaction Terms/Effects:						
RetailQspread (Reference Group)		1.0000				
ForeignQspread	0.2847***	1.3294	0.00316	90.0221	1.3212	1.3377
InstitutionQspread	0.2099***	1.2335	0.00467	44.9115	1.2223	1.2449
RetialWtime (Reference Group)		1.0000				
ForeignWtime	-0.1781***	0.8369	0.00489	-36.4162	0.8289	0.8449
InstitutionWtime	-0.2370***	0.7890	0.00936	-25.3304	0.7747	0.8036
RetialPvolat (Reference Group)		1.0000				
ForeignPvolat	-99.2710***	7.7117×10^{-44}	1.44606	-68.6491	4.5317×10^{-45}	1.3123×10^{-42}
InstitutionPvolat	2.2847***	9.8224	0.65629	3.4812	2.7138	35.5513
RetailDSameVol (Reference Group)		1.0000				
ForeignDSameVol	0.4843***	1.6230	0.01158	41.8149	1.5866	1.6603
InstitutionDSameVol	-0.1750***	0.8394	0.01444	-12.1219	0.8160	0.8635
RetailDOppVol (Reference Group)		1.0000				
ForeignDOppVol	0.5787***	1.7838	0.01314	44.0414	1.7384	1.8303
InstitutionDOppVol	1.2535***	3.5026	0.02416	51.8784	3.3406	3.6724
Intercepts:						
Intercept Cut 1	-1.1502***		0.00084	-1,369.4229		
Intercept Cut 2	-0.8492***		0.00082	-1,037.2535		
Intercept Cut 3	0.2003***		0.00081	248.6663		
Intercept Cut 4	0.2203***		0.00081	273.4186		
Observations		23,497,631				
R^2		0.02436				

Remarks: *p<0.05; **p<0.01; ***p<0.001.

Table 2.6: Ordered Logit Regressions: Selling Side

Independent Variables	Coefficient	Odds Ratio	Std. Error	t-Stat	Confidence Interval 2.5%	97.5%
Quote Spread (Qspread)	-0.4981***	0.6077	0.00308	-161.6285	0.6040	0.6113
Waiting Time (Wtime)	-0.2307***	0.7940	0.00411	-56.1716	0.7876	0.8004
Price Volatility (Pvolat)	-20.1410***	7.9399×10^{-9}	0.86948	-23.1643	3.2568×10^{-10}	9.8400×10^{-9}
Depth of the Same Side (DSameVol)	0.2006***	1.2221	0.00785	14.6663	1.2014	1.2432
Depth of the Opposite Side (DOppVol)	0.1151***	1.1220	0.00873	22.9656	1.1049	1.1394
d_R (Dummy for Retail Traders; Reference Group)		1.0000				
d_F (Dummy for Foreign Traders)	-0.2016***	0.8174	0.00128	-157.6775	0.8154	0.8195
d_I (Dummy for Institutional Traders)	0.5386***	1.7135	0.00174	310.3299	1.7077	1.7194
Interaction Terms/Effects:						
RetailQspread (Reference Group)		1.0000				
ForeignQspread	0.4965***	1.6429	0.00368	134.7631	1.6311	1.6549
InstitutionQspread	0.2083***	1.2315	0.00475	43.8009	1.2201	1.2431
RetialWtime (Reference Group)		1.0000				
ForeignWtime	-0.2541***	0.7756	0.00556	-45.6622	0.7672	0.7841
InstiututionWtime	-0.1971***	0.8211	0.00983	-20.0617	0.8054	0.8370
RetialPvolat (Reference Group)		1.0000				
ForeignPvolat	-158.4013***	1.6113×10^{-69}	1.36747	-115.8356	1.1045×10^{-70}	2.3505×10^{-68}
InstitutionPvolat	-41.9743***	5.8991×10^{-19}	0.83373	-50.3451	1.1511×10^{-19}	3.0231×10^{-18}
RetailDSameVol (Reference Group)		1.0000				
ForeignDSameVol	0.5778***	1.7822	0.01302	44.3823	1.7373	1.8283
InstitutionDSameVol	-0.1466***	0.8637	0.01751	-8.3681	0.8345	0.8938
RetailDOppVol (Reference Group)		1.0000				
ForeignDOppVol	0.3317***	1.3934	0.01237	26.8236	1.3600	1.4276
InstitutionDOppVol	0.7729***	2.1660	0.02210	34.9718	2.0741	2.2618
Intercepts:						
Intercept Cut 1	-1.3656***		0.00103	-1,332.0234		
Intercept Cut 2	-1.1335***		0.00101	-1,124.5996		
Intercept Cut 3	-0.1446***		0.00098	-147.3097		
Intercept Cut 4	-0.1263***		0.00098	-128.6350		
Observations		22,722,063				
R^2		0.02324				

Remarks: *p<0.05; **p<0.01; ***p<0.001.

Table 2.7: Marginal Effects of Ordered Logit Regressions: Buying Side

Independent Variables	Dependent Variable: Order Aggressiveness Order Type				
	Type 1 (Cancellation)	Type 2 (Bid Behind)	Type 3 (Bid At)	Type 4 (Bid Within)	Type 5 (Marketable Buy)
Quote Spread (Qspread)	0.052***	0.008***	0.011***	0.000***	-0.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	[122.815]	[122.008]	[121.246]	[-112.711]	[-122.807]
Waiting Time (Wtime)	0.033***	0.005***	0.007***	0.000***	-0.044***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[53.856]	[53.793]	[53.738]	[-52.902]	[-53.859]
Price Volatility (Pvolat)	5.589***	0.830***	1.139***	-0.016***	-7.542***
	(0.153)	(0.023)	(0.031)	(0.000)	(0.207)
	[36.427]	[36.407]	[36.391]	[-36.132]	[-36.428]
Depth of the Same Side (DSameVol)	-0.038***	-0.006***	-0.008***	0.000***	0.051***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
	[-30.218]	[-30.206]	[-30.193]	[30.050]	[30.218]
Depth of the Opposite Side (DOppVol)	-0.040***	-0.006***	-0.008***	0.000***	0.054***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
	[-29.946]	[-29.933]	[-29.918]	[29.784]	[29.945]
d_R (Dummy for Retail Traders)(Reference Group)					
d_F (Dummy for Foreign Traders)	0.031***	0.005***	0.006***	0.000***	-0.042***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[140.644]	[141.436]	[146.222]	[-121.944]	[-142.056]
d_I (Dummy for Institutional Traders)	-0.100***	-0.017***	-0.035***	0.000***	0.152***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[-401.600]	[-338.374]	[-266.423]	[-1.151]	[356.973]
Interaction Terms/Effects					
RetailQspread (Reference Group)					
ForeignQspread	-0.052***	-0.008***	-0.011***	0.000***	0.070***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[-90.024]	[-89.703]	[-89.410]	[85.788]	[90.022]
InstitutionQspread	-0.038***	-0.006***	-0.008***	0.000***	0.052***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[-44.913]	[-44.872]	[-44.831]	[44.357]	[44.911]
RetialWtime (Reference Group)					
ForeignWtime	0.033***	0.005***	0.007***	0.000***	-0.044***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[36.414]	[36.394]	[36.390]	[-36.100]	[-36.417]
InstiututionWtime	0.043***	0.006***	0.009***	0.000***	-0.059***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)
	[25.330]	[25.324]	[25.319]	[-25.228]	[-25.330]
RetialPvolat (Reference Group)					
ForeignPvolat	18.162***	2.697***	3.703***	-0.052***	-24.510***
	(0.265)	(0.039)	(0.054)	(0.001)	(0.357)
	[68.649]	[68.514]	[68.375]	[-66.730]	[-68.649]
InstitutionPvolat	-0.418***	-0.062***	-0.085***	0.001***	0.564***
	(0.120)	(0.018)	(0.024)	(0.000)	(0.162)
	[-3.481]	[-3.481]	[-3.481]	[3.481]	[3.481]
RetailDSameVol (Reference Group)					
ForeignDSameVol	-0.089***	-0.013***	-0.018***	0.000***	0.120***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)
	[-41.814]	[-41.781]	[-41.758]	[41.365]	[41.815]
InstitutionDSameVol	0.032***	0.005***	0.007***	0.000***	-0.043***
	(0.003)	(0.000)	(0.001)	(0.000)	(0.004)
	[12.122]	[12.121]	[12.120]	[-12.111]	[-12.122]
RetailDOppVol (Reference Group)					
ForeignDOppVol	-0.106***	-0.016***	-0.022***	0.000***	0.143***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)
	[-44.042]	[-44.003]	[-43.968]	[43.527]	[44.041]
InstitutionDOppVol	-0.229***	-0.034***	-0.047***	0.001***	0.309***
	(0.004)	(0.001)	(0.001)	(0.000)	(0.006)
	[-51.886]	[-51.816]	[-51.712]	[51.115]	[51.876]
Number of observations				23,497,631	

Remarks: *p<0.05; **p<0.01; ***p<0.001; values in () and [] stand for standard error and t-statistics, respectively.

Table 2.8: Marginal Effects of Ordered Logit Regressions: Selling Side

Independent Variables	Dependent Variable: Order Aggressiveness				
	Order Type				
	Type 1 (Cancellation)	Type 2 (Ask Behind)	Type 3 (Ask At)	Type 4 (Ask Within)	Type 5 (Marketable Sell)
Quote Spread (Qspread)	0.083***	0.011***	0.030***	0.000***	-0.124***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[161.625]	[159.277]	[160.167]	[115.744]	[-161.629]
Waiting Time (Wtime)	0.039***	0.005***	0.014***	0.000***	-0.058***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[56.168]	[56.070]	[56.119]	[53.257]	[-56.171]
Price Volatility (Pvolat)	3.366***	0.445***	1.214***	0.004***	-5.029***
	(0.145)	(0.019)	(0.052)	(0.000)	(0.217)
	[23.165]	[23.156]	[23.159]	[22.935]	[-23.164]
Depth of the Same Side (DSameVol)	-0.034***	-0.004***	-0.012***	0.000***	0.050***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)
	[-22.966]	[-22.959]	[-22.961]	[-22.740]	[22.966]
Depth of the Opposite Side (DOppVol)	-0.019***	-0.003***	-0.007***	0.000***	0.029***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
	[-14.666]	[-14.665]	[-14.665]	[-14.607]	[14.666]
d_R (Dummy for Retail Traders)(Reference Group)					
d_F (Dummy for Foreign Traders)	0.034***	0.004***	0.012***	0.000***	-0.050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[157.459]	[155.826]	[157.822]	[116.574]	[-157.935]
d_I (Dummy for Institutional Traders)	-0.081***	-0.012***	-0.039***	0.000***	0.132***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[-347.092]	[-303.564]	[-272.557]	[-159.049]	[320.822]
Interaction Terms/Effects					
RetailQspread (Reference Group)					
ForeignQspread	-0.083***	-0.011***	-0.030***	0.000***	0.124***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[-134.756]	[-133.383]	[-133.926]	[-104.679]	[134.763]
InstitutionQspread	-0.035***	-0.005***	-0.013***	0.000***	0.052***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[-43.801]	[-43.751]	[-43.772]	[-42.397]	[43.801]
RetialWtime (Reference Group)					
ForeignWtime	0.042***	0.006***	0.015***	0.000***	-0.063***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	[45.656]	[45.604]	[45.644]	[44.143]	[-45.662]
InstitutionWtime	0.033***	0.004***	0.012***	0.000***	-0.049***
	(0.002)	(0.000)	(0.001)	(0.000)	(0.002)
	[20.061]	[20.057]	[20.060]	[19.919]	[-20.062]
RetialPvolat (Reference Group)					
ForeignPvolat	26.469***	3.502***	9.547***	0.030***	-39.547***
	(0.229)	(0.030)	(0.083)	(0.000)	(0.341)
	[115.813]	[114.987]	[115.342]	[94.975]	[-115.836]
InstitutionPvolat	7.014***	0.928***	2.530***	0.008***	-10.480***
	(0.139)	(0.018)	(0.050)	(0.000)	(0.208)
	[50.335]	[50.282]	[50.325]	[48.209]	[-50.345]
RetailDSameVol (Reference Group)					
ForeignDSameVol	-0.097***	-0.013***	-0.035***	0.000***	0.144***
	(0.002)	(0.000)	(0.001)	(0.000)	(0.003)
	[-44.382]	[-44.330]	[-44.352]	[-42.867]	[44.382]
InstitutionDSameVol	0.024***	0.003***	0.009***	0.000***	-0.037***
	(0.003)	(0.000)	(0.001)	(0.000)	(0.004)
	[8.368]	[8.368]	[8.368]	[8.356]	[-8.368]
RetailDOppVol (Reference Group)					
ForeignDOppVol	-0.055***	-0.007***	-0.020***	0.000***	0.083***
	(0.002)	(0.000)	(0.001)	(0.000)	(0.003)
	[-26.824]	[-26.812]	[-26.817]	[-26.477]	[26.824]
InstitutionDOppVol	-0.129***	-0.017***	-0.047***	0.000***	0.193***
	(0.004)	(0.000)	(0.001)	(0.000)	(0.006)
	[-34.974]	[-34.948]	[-34.951]	[-34.158]	[34.972]
Number of observations					22,722,063

Remarks: *p<0.05; **p<0.01; ***p<0.001; values in () and [] stand for standard error and t-statistics, respectively.

2.6 Conclusion

This study examines the various trading decisions employed by different types of investor in the Thailand stock market, focusing on their varying levels of order aggressiveness and the influence of market conditions on their trading behaviours. The study employs ordered logit regression and analyses marginal probabilities, utilising trading data from the SET100 index, encompassing 100 stocks, during the period from July to December 2019.

Distinct order submission aggressiveness emerges among traders in the Thailand stock market. Foreign traders, identified as faster traders employing market timing strategies, exhibit strategic order submission aggressiveness tactics in response to market conditions. Their sensitivity to non-execution costs prompts swift adjustments to pending orders, transitioning from cancellations to more aggressive resubmissions. They strategically respond to factors such as increased bid-ask spread and reduced market liquidity with heightened aggressiveness. In situations where more orders are placed on their side, indicating increased competitiveness, they pursue order submission aggressiveness by cutting in line or staying ahead. Conversely, they adopt passive orders when the market on their side is thinning, focusing on avoiding the picking-off risk associated with heightened volatility.

Institutional traders adapt their order submission aggressiveness based on market factors, particularly transient volatility. During highly volatile market periods, their selling orders adopt a passive stance in response to increased market volatility, as institutions seek to control the risk of picking off on the selling side. Retail traders, trading at a slower pace, are anticipated to incur costs relating to non-execution and picking-off on both the buying and selling sides.

Chapter 3

Learning Effects in Repeated Market-Wide Circuit Breakers

3.1 Introduction

Market-wide Circuit Breakers ("MWCBs") are temporary pauses to the trading of all stocks on an exchange intended to stabilise markets under extreme conditions.[1] The period during which trading is interrupted allows market participants time to revise their submitted orders or reconsider their trading strategies (Ackert, 2012; Subrahmanyam, 2017). Since their first use in the US on Black Monday in 1987, MWCBs have been used in trading venues worldwide to control volatility, e.g., during the Global Financial Crisis, (2007-9), the European Sovereign Debt Crisis (2011-2012), and the Covid-19 pandemic (Brady, 1988; Gomber et al., 2016; Alderighi, 2021).

There is mixed opinion as to the effectiveness of MWCBs. On the one hand, MWCBs can deflate stock market volatility (e.g., Kyle, 1988; Santoni and Liu, 1993; Goldstein, 2015), facilitate the adjustment of stock prices towards a new equilibrium (Corwin and Lipson, 2000; Engelen and Kabir, 2006; Hausser et al., 2006; Madura et al., 2006 and Wong et al., 2009), enhance trading volumes (Greenwald and Stein, 1991; Ferris et al., 1992; Corwin and Lipson, 2000; Li and Yao, 2021), and lead to more informative stock prices (e.g., Lin et al., 2022). However, MWCBs can also increase volatility once trading resumes (Kryaznowski and Nemiroff, 2001; Bildik and Gulay, 2006; Danisoglu and Guner, 2016), and generate illiquidity risk or delay price discovery (Wong et al., 2009).

It was not until the sharp selloffs during the first Covid-19 lockdowns in March 2020 that MWCBs were triggered on a global basis. In Thailand, plummeting prices led to a series of interventions during March 2020 as the Stock Exchange of Thailand (the "SET")

[1] Single stock circuit breakers halt trading only for particular stocks.

attempted to calm the Thai market. During that month, MWCBs were used three times. First, on 12th March, trading was halted for 30 minutes after the SET index fell by approx. 10%. Continued declines in the European and US stock markets led to a second MWCB the following day on 13th March 2020, only 2 minutes into the morning trading session. Due to enormous imbalances caused by sell-side pressure, on 13th March the SET also announced a temporary change to its short-selling rule (from a "zero-plus tick" to an "uptick" rule). On 18th March, the SET went even further, narrowing the range of index price movements triggering future MWCBs and the limit up-limit-down rule. Finally, on 23rd March, a third MWCB was triggered.

Repeated use of MWCBs in close succession by a single exchange to restore normal market function is rare. Moreover, only the overall/aggregate market impact of MWCBs applied in series has been studied so far, i.e., without isolating the *individual* effects of each MWCB (e.g., Moise, 2022). Hence, the extent to which traders modify their response to MWCBs based on their experience of earlier MWCBs within a sequence of applications is unexplored. In this paper, using data from the Thai market during March 2020, we evaluate these learning effects. Our analysis is important because ex-ante, the impact of MWCBs on the markets is uncertain. In Thailand, it is evident, *prima facie*, that the first two MWCBs in March 2020 were insufficient to recover market quality: hence, a third MWCB ensued. Whilst the first two MWCBs may have somewhat contributed to improving market quality, the third MWCB was conclusive. However, the application by the SET of a third MWCB was also risky; had the market not sufficiently calmed after the third MWCB, this mechanism may have lost credibility.

To investigate learning effects in serial MWCBs, we apply panel regressions to all of the stocks comprising the SET100 index at 1-minute trading intervals. Panel regression and difference-in-difference (DID) models are used to evaluate the impacts of the first (12th March) and third (23rd March) MWCBs on 11 different measures of market quality. These measures capture changes to market conditions due to MWCBs by comparing the 30-minute period immediately after trading resumed with the 30-minute trading period just before the circuit breaker was triggered. Because the second MWCB (on 13th March 2020) occurred only 2-minutes into the start of the morning trading session, there is no trading period of sufficient duration just prior to the trading halt on that day to measure the impact of the second MWCB on market quality; hence, the second MWCB is not tested. Although this study primarily measures the average effects on 11 different measures of market quality without directly analysing how learning influences trading behaviour, it still offers sufficient evidence to imply the learning effects of traders during the serial MWCBs. This implication arises because repeated exposure to MWCBs likely allows traders to adapt their trading strategies and responses over time, even if the study does not explicitly track these behavioural changes in trading.

Our results show that in March 2020, the third MWCB was effective at restoring market quality, whereas the first MWCB was ineffective. DID results for the third MWCB versus the first MWCB show that liquidity returned to the market and volatility reduced, irrespective of the measure used for each effect. For example, the Amihud illiquidity measure is positive for the first MWCB, but negative for the third MWCB, both results significant at 1%. The relative effectiveness of the third MWCB in reducing market volatility is similarly supported in the baseline panel regression; whilst both the first and third MWCBs had a significant volatility-reducing impact on prices (at the 1% level), coefficients for realised variance and jump variation are 4.0 times and 2.3 times smaller (resp.) for the third MWCB relative to the first MWCB. Also, order imbalance is insignificant for the third MWCB but significant for the first MWCB. These results show that whilst the first MWCB was ineffective, it nevertheless conditioned traders via a learning effect to respond dissimilarly to the third MWCB, thereby enabling the SET to finally restore market quality.

This paper makes several contributions. As far as we are aware, ours is the first analysis of the separate learning effects of individual MWCBs within a sequence of repeated applications used to restore market quality. By quantifying the relative effectiveness of later versus earlier MWCBs, our results directly inform policies governing the sequential use of MWCBs, and in particular, the trade-off between the potential benefits of repeating their application versus associated costs and risks. Second, whilst there is a large literature on the effectiveness of single-shot MWCBs, our paper opens up a line of research previously not investigated, namely, learning (and possibly other) effects manifesting in the repeated/serial use of MWCBs. Third, our findings imply that learning effects have the potential to reconcile divergent results in the literature as to the effectiveness of MWCBs by endogenising them in effectiveness studies.

The rest of the paper is as follows. Section 3.2 reviews the literature. Section 3.3 details data and provides a chronology of MWCBs and regulatory changes during March 2020 in Thailand. Section 3.4 explains the methodology. Section 3.5 presents results. Section 3.6 concludes.

3.2 Literature Review

We now review the theoretical and empirical literature on the effectiveness of market-wide circuit breakers at restoring market quality following a period of extreme volatility. Both theoretical and empirical studies provide mixed evidence. We also document how learning effects arise in trading generally.

3.2.1 Theoretical Evidence on the Effectiveness of MWCBs

Opponents of circuit breakers argue that mandated trading halts are unnecessary, as they disrupt the natural price movement of securities. Theoretical models in Subrahmanyam (1994, 1995) suggest that circuit breakers may inadvertently increase price variability due to the so-called "magnet effect", which occurs because market participants rush to execute their trades before a circuit breaker triggers a halt to trading. Subrahmanyam (1997) also suggests the existence of an asymmetry amongst traders due to MWCBs, whereby informed traders reduce their trading activities in anticipation of a trading halt, leading to higher trading costs for small investors. The effects of price limits on information quality and dissemination have also been investigated theoretically. For example, Anshuman and Subrahmanyam (1999) suggest that price limits could lower information quality whilst simultaneously improving liquidity by reducing bid-ask spreads. In contrast, Kim and Sweeney (2002) find that price limits may slow down information dissemination and reduce market efficiency.

In contrast to the above, some theoretical results instead support circuit breakers. For instance, Kyle (1988) confirms that MWCBs can reduce volatility and order imbalances by providing a "cooling-off period," which may prevent unwarranted price changes. Greenwald and Stein (1991) suggest that mandated halts can play a useful role in reducing transaction risk, particularly when there is uncertainty about execution prices; these authors also suggest that circuit breakers encourage buyers and sellers to submit orders, thereby stimulating value-buyer responsiveness. Furthermore, Kodres and O'Brien (1994) indicate that price limits promote risk sharing, especially when price shocks occur before traders can execute their desired trades. Lastly, Westerhoff (2003) argues that if investors chase price trends, then price limits help reduce the deviation of market prices from fundamental values.

Overall, the theoretical literature on circuit breakers is mixed. Since theoretical models are based on specific assumptions, their capacity to explain more general settings is necessarily also limited. Hence, theoretical evidence as to the effectiveness of trading halts should be carefully considered in each specific market context/condition before extrapolating to other settings.

3.2.2 Empirical Evidence on the Effectiveness of MWCBs

A considerable empirical literature examining trading interruptions and price limits in various international stock exchanges finds that price limits often fail to reduce volatility (Kuhn et al., 1991; Switzer and Yue, 2019), and in some cases, even exacerbate it (Ferris et al., 1992; Lee et al., 1994; Corwin & Lipson, 2000). This pattern is evident in stock exchanges internationally, including China (Li et al., 2021), Hong Kong (Wu, 1998), Montreal and Toronto (Kryzanowski and Nemiroff, 2001), Istanbul (Bildik and Gulay, 2006; Danisoglu and Guner, 2016), Taiwan (Chen, 1993), and Thailand (Kim, 2001). In the Tokyo Stock Exchange, Kim and Rhee (1997) find that circuit breakers fail to curb excess volatility, creating volatility spill-overs into subsequent trading sessions.

Beyond volatility effects, circuit breakers may also impede the price discovery process (e.g., Corwin and Lipson, 2000; Chan et al., 2005). Yoon (1994)'s findings indicate that prices may "overshoot" fundamental values in the presence of circuit breaker rules. Corwin and Lipson (2000) identified price discovery delays and illiquidity due to a surge in order activity during and after trading halts, whilst Chan et al. (2005) confirm that price limits significantly reduce price informativeness.

In addition to empirical literature reporting the ineffectiveness of circuit breakers, there is a substantial literature evidencing the contrary. Lauterbach and Ben-Zion (1993) suggest that trading halts contribute to price adjustment smoothing and the mitigation of order imbalances. Some literature also reports that trading halts might even enhance the price discovery process (Engelen and Kabir 2006; Hausser et al., 2006; Madura et al., 2006; Lin et al., 2022), and effectively stabilise markets, especially during extreme market movements (Santoni and Liu, 1993; Li and Yao, 2021).

More recently, other aspects related to circuit breakers have also been explored. These include the importance of circuit breaker parameter values in determining their overall effectiveness, such as duration and triggering thresholds (e.g., Clapham et al., 2017; Sifat and Mohamad, 2020), volatility spillovers between markets (Goldstein, 2015), and trading conservatism induced by circuit breakers (Hu, 2020). Sifat and Mohamad (2020) find that upper limits can dampen volatility with minimal trading interference in calm markets, while lower limits produce mixed results. Goldstein (2015) finds that stock market circuit breakers reduce volatility spillovers to the futures market. Hu (2020) finds that informed investors adopt more conservative strategies, and trade in smaller sizes when circuit breakers are in effect.

In common with theoretical studies, empirical studies on the effectiveness of circuit breakers are also inconclusive. The existence of mixed evidence in the literature adds importance to our particular line of enquiry, namely, to compare the impact of circuit breakers within a series, and their capacity to modify trading behaviour through a learning effect. Moreover, none of the aforementioned studies investigate repeated circuit breakers; indeed, even for settings in which multiple circuit breakers have been used by an exchange, there is no attempt to compare the individual impacts of successive MWCBs on trading behaviour (Moise, 2022). Instead, serial MWCBs are treated as a single trading interruption, with comparisons of market quality made between the period just before the first MWCB, and immediately after the last.

3.2.3 Learning Effects in Trading

The extent to which traders internalise information about changing market conditions, and what they learn from their trading experiences, each have a bearing on how traders adapt their strategies over time. Specifically, whether/how traders internalise new information (about market conditions and from lessons learned) informs how they may respond to a single versus a serial application of MWCBs. This is because many traders have no prior experience of MWCBs. Consequently, earlier MWCBs in a series may condition traders to react differently to later MWCBs, with fewer panic transactions due to an already established familiarity with trading halts. Alternatively, such conditioning may be weak or even absent, with panic trades continuing after the next circuit breaker. Both of these viewpoints are supported in the literature. Investigating the effects of individuals MWCBs in a series allows us to better understand this important issue.

We next turn to theories of how traders learn. Research in finance and behavioural economics has identified four distinct theories: cognitive biases in learning; learning from experience; adaptive trading strategies; and learning from feedback.

3.2.3.1 Cognitive Bias

Cognitive bias relates to how traders learn from their successes and failures. Early research by Shefrin and Statman (1985) and Odean (1998) found evidence of the so-called "disposition effect", in which investors prematurely sell winning stocks and hold on to losing stocks. Consistent with this effect, Jegadeesh and Titman (1993) find that investors who buy past winners and sell past losers generate positive returns. Each of these studies concludes that traders may not always learn from past experiences. In turn, this indicates that in a series of temporary trading interruptions, later MWCBs may induce responses in traders that differ significantly from earlier MWCBs.

3.2.3.2 Learning by Experience

Barber and Odean (2000) investigate how the length of trading experience influences investment performance; they find that inexperienced investors tend to underperform the market. Gervais and Odean (2001) and Menkhoff et al. (2013) conclude that overconfidence in early-career investors diminishes as experience increases. These studies indicate that traders learn as they become more seasoned investors. Notably, even though the timeframe over which seasoning occurs exceeds the short intervals between MWCBs in series, such as in Thailand during March 2020, these studies nevertheless indicate that due to a learning effect, earlier trading interruptions may induce a dissimilar response to later MWCBs when trading halts are repeated.

3.2.3.3 Adaptive Trading Strategies

Adaptive trading strategies are those for which traders continuously refine their strategies in response to changing market conditions. Internalising new market information within trading decisions necessarily indicates that learning is taking place. Learning efficiency, however, varies as to the specific process used to internalise new information. An example is algorithmic trading, which employs real-time monitoring of the limit order book to determine optimal times to provide or take liquidity (Hendershott et al., 2011). Furthermore, adapted trading strategies based on machine learning algorithms outperform more conventional trading methods (Alessandretti et al., 2018).[2] If traders continuously adapt their trading strategies in response to new information, then earlier MWCBs in March 2020 would necessarily create a learning effect that alters their response to the third MWCB; however, the extent to which alteration arises depends on learning efficiency: a delayed or partial learning effect would have a lesser impact.

3.2.3.4 Learning from Feedback

Learning from feedback refers to systematically reviewing past trading decisions and outcomes to identify strengths and weaknesses in trading strategies (e.g., De Long et al., 1990; Nofsinger and Sias, 1999; Greenwood and Shleifer, 2014). How feedback is used depends on investor type. For example, positive feedback, in which traders buy additional securities in response to previous price increases, is found in small investors and speculators, whereas a contrarian response is found in hedgers (Röthig and Chiarella, 2010; Smales, 2015).

Overall, whilst a considerable amount of literature finds that traders adapt their strategies based on past performance (i.e., learning from feedback and learning by experience) and changing market conditions (i.e., adaptive strategies), cognitive bias presents a notable exception. It is therefore not possible to conclude from the literature whether earlier MWCBs in a series of repeated applications would unequivocally condition traders to respond dissimilarly to later MWCBs, nor whether if they were eventually to respond differently, for which MWCB in a series (e.g., second, third etc.) this would most likely happen.

3.3 Interventions and Trading Data

This section details how the SET attempted to control extreme volatility during March 2020 using MWCBs and targeted changes to trading rules. A description of SET trading data is also provided.

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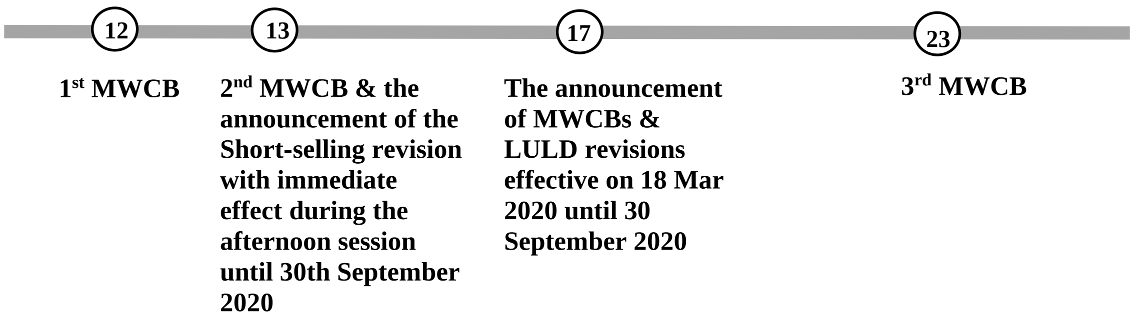
[2] Other studies which explore the dynamic optimisation of trading strategies include Obizhaeva and Wang (2013) in the context of supply and demand dynamics, and Bertsimas and Lo (1998) regarding the minimisation of costs attributable to the execution of block trades.

3.3.1 Interventions

Figure 3.1 provides a timeline of SET interventions in March 2020, namely, three MWCBs and a temporary revision to trading rules related to short-selling and the limit up-limit down (LULD) rule.

Figure 3.1: Timeline of MWCBs and Regulatory Changes During March 2020



MWCBs lasting 30-minutes were triggered on: 12^{th} March; 13^{th} March; and 23^{rd} March. Concerning short-selling rules, prior to 13^{th} March 2020, the SET mandated the “zero-plus tick” rule, whereby traders cannot short-sell at a price below the last executed price. However, during the intermission following the morning trading session on 13^{th} March, i.e., just after the second MWCB, the SET replaced this with the “uptick” rule until 30^{th} September 2020, in which short sales would only be possible at a price higher than the last quote, or at the offer price.

After the failure of the first two MWCBs and the new short-selling rule to sufficiently calm the markets, on the evening of 17^{th} March the SET announced changes to the limit up-limit down (LULD) rule effective from 18^{th} March to the end of September 2020. These changes narrowed the range of price movements at which *single security* circuit breakers would be triggered for listed Thai stocks, foreign stocks, and futures.

Table 3.1 summarises changes to the single security limit up-limit down rules by security type:

Table 3.1: Changes to Single Security Limit-up Limit-down Rules by Security Type

Type of Security	Current rule	New rule	Base
A. General securities	+/- 30%	+/- 15%	% of the previous day's closing price
B. Securities held by foreign nationals	+/- 60%	+/- 30%	% of the previous day's closing price
C. Transferable subscription rights D. Derivative warrants and other warrants	+/- 30%	+/- 15%	% of the previous day's closing price multiplied by a conversion ratio

On 17th March, the SET also raised the MWCB price floor triggers, and increased the number of permissible MWCBs per day from two to three. The trigger price decrease (relative to the previous day's closing index) for the first MWCB was changed from -10% to -8% (30-minute trading halt); the second MWCB floor was changed from -20% to -15% (30-minute trading halt); and the possibility of a third MWCB in the same day was introduced with a floor of -20% (60-minute trading halt). Lastly, if a third MWCB were to be triggered on the same day, the SET would continue matching orders until the close of the market session, with no further halts.

3.3.2 Regulatory Changes

As detailed above, there were two sets of regulatory rule changes: the short-selling rule was changed on 13th March; changes to the LULD thresholds and MWCB rules were announced on 17th March effective the following day. Whilst these changes were introduced between the first and third MWCBs, we argue in the following that they do not compromise our analysis of possible learning effects created by the first MWCB influencing traders' responses to the third MWCB.

First consider rule changes other than for MWCBs, i.e., short-selling and LULD. These new rules were in place during the 5-days days prior to the third MWCB and applied to trading in *both* sample periods immediately before and after (i.e., either side of) the third MWCB. Therefore, these rule changes do not affect the impact on market quality of the third MWCB as they are common to both periods (neither do they impact the first MWCB which pre-dates them).

Next, consider the elevation of the MWCB price floor and increase in the number of permissible MWCBs per day. It is rational for traders to have increased the probability assigned to future MWCBs as a result of these changes, and in particular, a third MWCB occurring during March 2020 given continued high market volatility (after the first two MWCBs). As a result, traders may have adapted their trading strategies in the period after these rule changes, e.g., by bringing forward planned trades. However, provided the announcement of a third MWCB was not leaked in advance, it was still an unpredictable event. Given that the third and first MWCBs interrupted trading for equal durations lasting 30-minutes each, the resulting impact of the third MWCB on market quality relative to that of the first MWCB captures only learning effects created by the first MWCB, and not the impact of changes to MWCB rules.

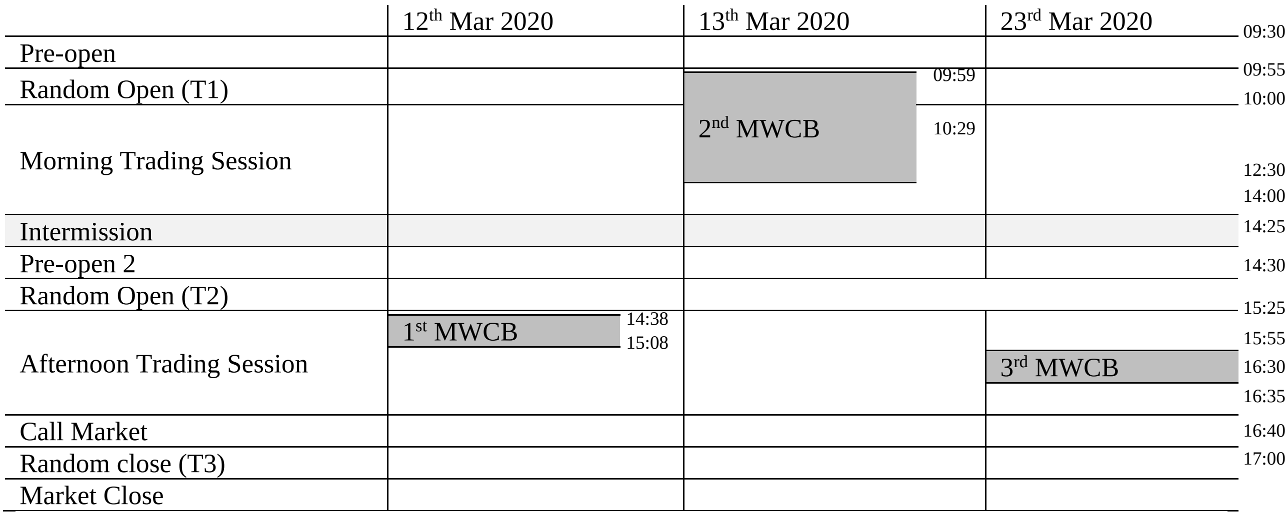
3.3.3 Data

We obtained trading data from the Stock Exchange of Thailand (SET) for the 30-minutes immediately before and after each MWCB on 12th March and 23rd March 2020 for all of the stocks comprising the SET100 Index. Trading data are at 1-minute intervals, and include precise timestamps, records of submitted, executed, and cancelled orders, buy and sell orders, company codes, trade prices, and trade volumes. SET100 stocks that underwent splits or were delisted during the observation period were excluded from our analysis.

The SET trading day comprises two main sessions: a morning session from 9:30 a.m. to 12:30 p.m. and an afternoon session from 2:00 p.m. to 4:30 p.m. The morning session is influenced by the preceding day's trading in US and Asian stock markets, including the Hong Kong and Japanese exchanges, while the afternoon session is typically influenced by European stock markets.

The morning session consists of the initial auction period from 9:30 a.m. to the T1 period. During this phase, traders can only submit their orders and await the T1 period, which the SET opens randomly between 9:55 a.m. and 10:00 a.m., establishing the daily opening price for each stock. Subsequently, traders can place orders following the price and time priority trading rule until the morning session concludes at 12:30 p.m. After a 90-minute break, trading resumes in the afternoon session at 2:00 p.m. This afternoon session commences with a second auction that lasts until the T2 period. The SET again opens the T2 period randomly between 2:25 p.m. and 2:30 p.m., establishing the opening price for each stock. Traders can submit orders adhering to the price and time priority trading rule until 4:30 p.m. Following this, the call market period, i.e., the third auction period, commences. During this phase, traders can enter their orders but must await execution by the SET during the T3 period, which occurs between 4:35 p.m. and 4:40 p.m., with the daily closing price for each stock. The SET's trading session then concludes.

Figure 3.2: Trading Sessions and MWCBs for the 12th, 13th and 23rd March 2020



3.4 Methodology

To evaluate the extent to which the first MWCB (on 12th March) may have conditioned the behaviour of traders via a learning effect to respond differently to the third MWCB (on 23rd March), we estimate the separate impact of each MWCB on market quality using a baseline model, and apply a Difference-in-Differences (DID) model to directly estimate the effect of the third MWCB relative to the first MWCB. We run separate estimations for both the baseline and DID models using 11 different measures of market quality as dependent variable.

3.4.1 Baseline Model

Our baseline model (3.1) follows Goldstein and Kavajecz (2004), Goldstein (2015), Cui and Gozluklu (2016), Switzer and Yue (2019), and Li and Yao (2021) to measure the separate impact of MWCBs on 12th and 23rd March 2020 on market quality. We use panel data for the SET100 index stocks and 30-minute trading periods immediately before and after MWCBs were triggered:

$$\mathrm{MQ}_{i,t} = \varphi_i + \theta \mathrm{CB}_{i,t}^{\mathrm{POST}} + \delta_{i,t} + \delta_{i,t}^2 + \mu_{i,t} \quad (3.1)$$

$\mathrm{MQ}_{i,t}$ measures the market quality of each stock i at time t using 11 different variables (our DID model uses the same 11 market quality variables). These are: Liquidity measures: quoted spread (QS), effective spread (ES), realised spread (RS), price impact (PI), Amihud illiquidity measure (AMH); Return measure: stock returns (RT); Volatility measures: realised variance (RV), bipower variation (BV), jump variation (JV), order imbalance (OI); Informed trading measure: volume-synchronised probability of informed trading (PIN). See Table C.1 in the Appendix for definitions. $\mathrm{CB}_{i,t}^{\mathrm{POST}}$ is a dummy variable equal to 1 in the 30-minute period immediately after a MWCB is triggered and zero in the 30-minute period immediately prior. $\delta_{i,t}$ is the time-of-the-day effect in minutes for each stock; $\delta_{i,t}$ is negative before a MWCB, positive after, and we exclude $\delta_{i,t} = 0$ from the analysis, i.e., $\delta_{i,t} = -30, -29, \dots, -1, +1, \dots, +29, +30$. $\mu_{i,t}$ is the idiosyncratic error for stock i at time t.

3.4.2 Difference-in-Differences (DID) Model

Following Goldstein and Kavajecz (2004), and Li and Yao (2021), our DID model specification is (3.2) below:

$$\mathrm{MQ}_{i,t,s} = \alpha + \beta \mathrm{Treat}_{i,s} + \gamma \mathrm{CB}_{i,t}^{\mathrm{POST}} + \mathrm{DID}\left(\mathrm{Treat}_{i,s} \times \mathrm{CB}_{i,t}^{\mathrm{POST}}\right) + \Gamma_i + \Gamma_s + \delta_{i,t} + \delta_{i,t}^2 + \varepsilon_{i,t,s} \quad (3.2)$$

$\mathrm{MQ}_{i,t,s}$ measures market quality for stock i at time t during event s. s is two events: event one is the first MWCB on 12th March 2020, which is used as the counterfactual[3]; event two is the third MWCB on 23rd March 2020, and comprises the treatment. The study employed the first MWCB as a counterfactual because the SET imposed a revised regulation of the MWCB after the first MWCB (MWCB-1) and before the third MWCB (MWCB-3).

[3] Li and Yao (2021) constructed the counterfactuals as events where the S&P500 index fell by more than a 7% threshold for the second time on the same day to compare with MWCB on the same day as the treatments. This construction of the counterfactuals and treatments aims to investigate what would happen to market quality in the absence and presence of the MWCBs. In contrast to our study, our construction of counterfactual and treatment is to investigate what happened to market quality due to MWCB-1 versus MWCB-3. By doing this, we set MWCB-1 as the counterfactual and use MWCB-3 as the treatment.

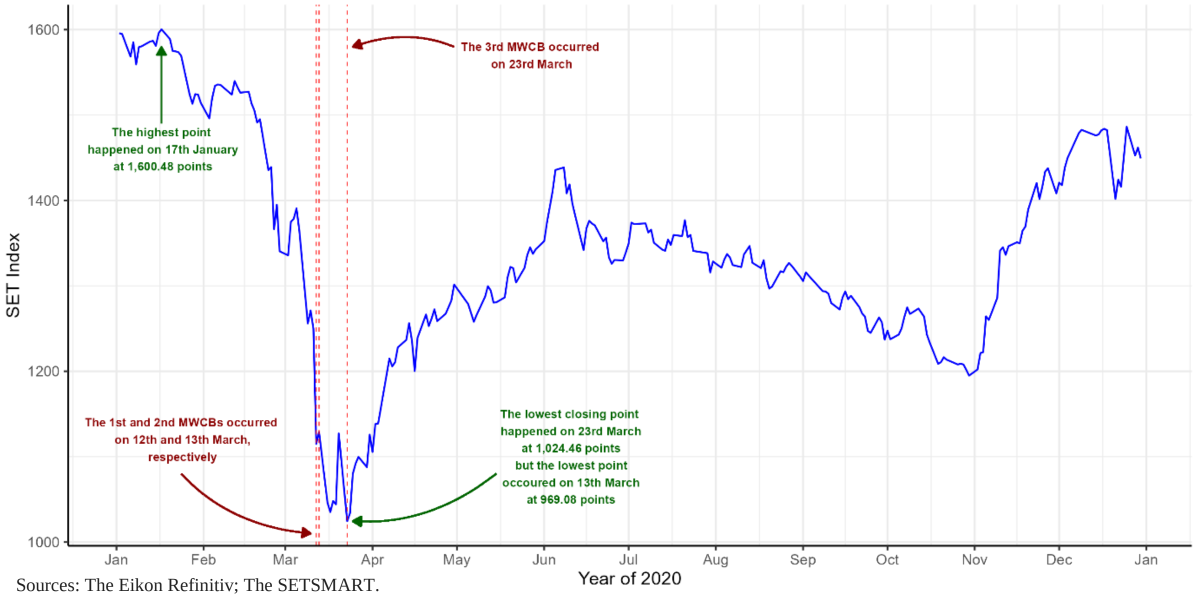
This revision of MWCB regulation would indirectly impact the learning effects of the traders in serial MWCBs, especially the adaptive trading strategies of traders in response to revised MWCB regulations in the Thai stock market. α is the intercept term. $\mathrm{Treat}_{i,s}$ is a dummy variable for stock i during event s equal to 1 on 23rd March 2020, and 0 on 12th March 2020. $\mathrm{CB}_{i,t}^{POST}$ is a dummy variable for stock i at time t equal to 1 for the 30-minute periods after the trading halts triggered by each MWCB and 0 for the 30-minute periods just prior. DID is the coefficient of the difference-in-differences (DID) estimation, which captures the effect of triggering the third MWCB on market quality on 23rd March 2020 as the treatment relative to the first MWCB on 12th March 2020 as the counterfactual. Γ_i is a stock fixed effect. Γ_s is a date fixed effect. $\delta_{i,t}$ is the time-of-the-day effect. $\varepsilon_{i,t,s}$ is the error term.

3.5 Results

3.5.1 Price Charts

Figure 3.3 charts the daily closing price of the SET index for the 12-month period from January to December 2020. This chart illustrates significant price fluctuations, in which the SET index reached its highest calendar year level of 1,600.48 on January 17, 2020, then declined sharply to reach its lowest level for 2020 of 1,024.46 on 23rd March, being 576.02 points, or -56.23%, below the year’s peak.

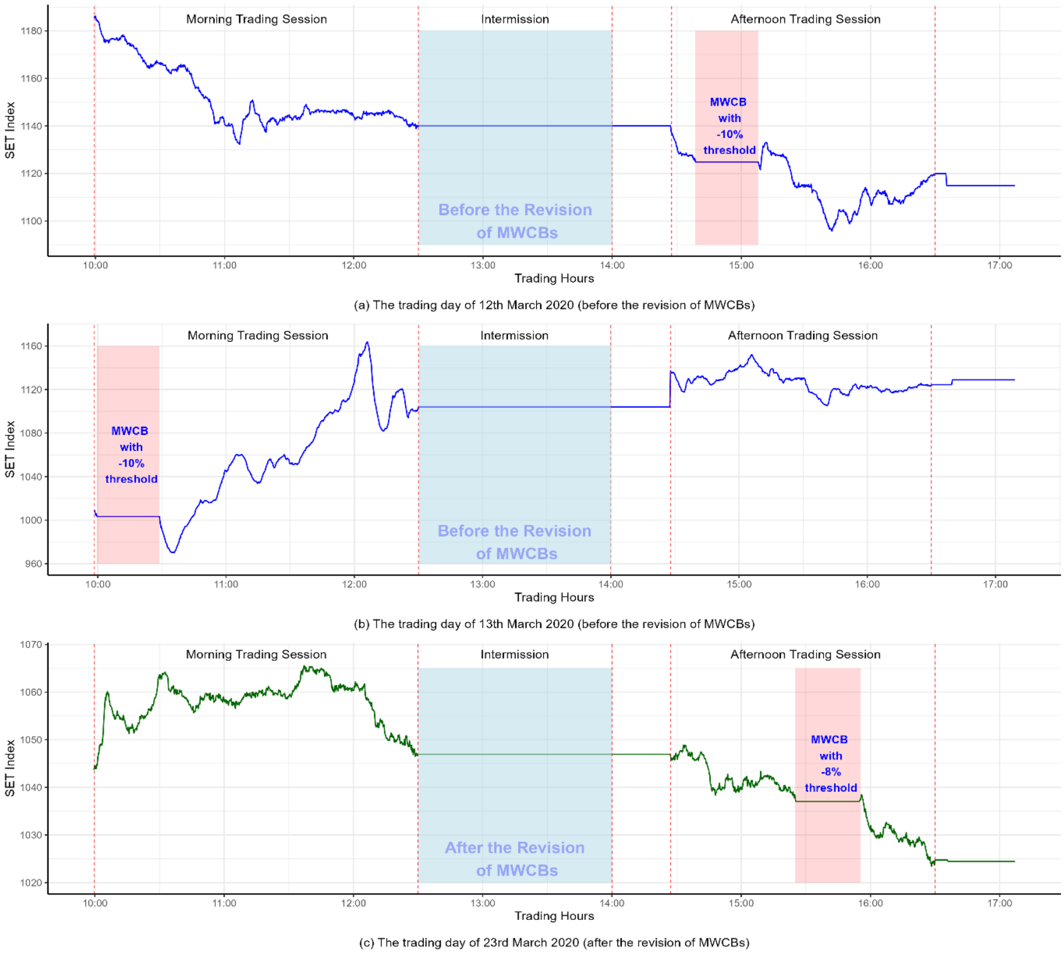
Figure 3.3: Daily Closing Prices of the SET Index for 2020



Sources: The Eikon Refinitiv; The SETSMART.

Figures 3.4a, 3.4b and 3.4c show SET index prices on each of the days that MWCBs were triggered.

Figure 3.4: SET Index Prices and MWCBs on (a) 12th March, (b) 13th March, and (c) 23rd March 2020



(a) The trading day of 12th March 2020 (before the revision of MWCBs)

(b) The trading day of 13th March 2020 (before the revision of MWCBs)

(c) The trading day of 23rd March 2020 (after the revision of MWCBs)

From charts 3.4a-3.4c, we highlight the following. The second MWCB on 13th March was triggered only 2-minutes into the morning trading session; this MWCB was influenced by the halt to trading during the previous day in the US stock market that occurred overnight in Thailand. During the intermission between the morning and afternoon trading sessions on 13th March, the SET announced changes to the short-selling rule with immediate effect. We speculate that news of this rule change may have been leaked prior to its announcement given the enormous flow of buy orders we observe in the data from traders trying to close out their short positions during the morning trading session; these buy orders would have caused the SET index price to increase, as seen in Fig. 3.4b.

3.5.2 Summary Statistics

Table 3.2 reports summary statistics on 12th March and 23rd March 2020 for the price, volume, and value of shares comprising the SET100 index, and each measure of market quality.

Table 3.2: Summary Statistics

Variables	Mean	Min	Max	Std	Skewness	Kurtosis
Panel A 12th March						
Price	31.34	0.35	299.00	44.51	3.20	15.56
Volume	67.74	1.00	32976.00	43708.96	38.18	2130.66
Value	81.65	0.04	10800.00	281445.80	13.14	295.77
Quoted Spread (QS)	36.21	12.52	350.88	18.50	3.11	19.96
Effective Spread (ES)	9.50	-252.87	792.29	40.51	0.06	9.84
Realised Spread (RS)	10.58	-2404.18	2397.66	91.77	2.15	205.74
Price Impact (PI)	-0.02	-53.29	55.92	1.88	-1.83	272.05
Amihud Illiquidity (AMH)	13.24	0.00	771.65	36.96	13.18	239.69
Return (RT)	-0.03	-4.72	5.16	0.40	-0.63	15.30
Realised Variance (RV)	0.04	0.00	0.66	0.05	3.39	22.73
Bipower Variation (BV)	1.00	0.00	7.74	1.05	1.39	5.86
Jump Variation (JV)	1.19	0.00	4.67	0.79	0.44	3.42
Order Imbalance (OI)	11.29	-10724.40	34805.20	651.73	15.17	646.89
Probability of Informed Trading (PIN)	0.60	0.21	0.98	0.13	0.23	2.62
Panel A 23rd March						
Price	29.70	0.31	297.00	45.41	3.36	16.26
Volume	50.23	1.00	22173.00	35571.05	36.93	1866.96
Value	55.44	0.03	8250.00	194353.80	13.62	339.06
Quoted Spread (QS)	35.74	12.52	229.51	17.79	3.72	24.82
Effective Spread (ES)	10.34	-222.22	282.13	38.79	-0.19	4.32
Realised Spread (RS)	9.98	-351.91	355.73	41.57	-0.09	5.31
Price Impact (PI)	0.01	-7.75	7.48	0.54	0.13	23.37
Amihud Illiquidity (AMH)	13.44	0.00	1185.76	47.90	17.61	401.57
Return (RT)	-0.06	-43.61	24.34	1.12	-21.29	629.64
Realised Variance (RV)	0.38	0.00	19.13	1.70	6.75	55.59
Bipower Variation (BV)	0.78	0.00	16.31	1.48	4.10	27.99
Jump Variation (JV)	2.49	0.00	43.63	5.38	4.36	23.79
Order Imbalance (OI)	3.69	-11142.30	83003.70	738.41	66.69	7179.80
Probability of Informed Trading (PIN)	0.65	0.24	1.00	0.14	0.07	2.56

From Table 3.2, we observe the following concerning the SET100 index and mean values of market quality variables for 12th March versus 23rd March.

The SET 100 index price fell by 5.23% from 31.34 THB on 12th March to 29.70 THB on 23rd March. This fall corresponds with a 25.85% decrease in trading volume from 67,740 shares on 12th March to 50,230 shares on 23rd March, and a fall in value from 81,650 THB to

55,440 THB. Given the first Covid-19 lockdown occurred in Thailand on 11th March 2020[4], these statistics likely reflect the abstention of traders from the market to control risks.

Concerning volatility on 23rd March versus 12th March, a higher realised variance (0.38 versus 0.04), higher jump variation (2.49% versus 1.19%) and lower bipower variation (0.78% versus 1.00%) indicate heightened uncertainty on 23rd March, consistent with a (slightly) higher Amihud illiquidity value (i.e., 13.44 versus 13.24).

Order imbalance (OI) statistics imply higher selling pressure on 12th March versus 23rd March. OI values are positive on both 12th and 23rd March, i.e., there is selling pressure on both days. However, OI is 3,690 shares on 23rd March, which is considerably lower than 11,290 shares on 12th March.

The probability of informed trading (PIN) captures information asymmetry due to the observed order imbalance caused by informed traders (Easley et al., 1996 and 1997). A higher PIN value of 0.65 on 23rd March versus 0.60 on 12th March is consistent with higher transaction costs (wider spread) and greater illiquidity on 23rd March.

Lastly, Table 3.2 also reveals changes to direct measures of market liquidity. The quoted spread marginally decreased by 1.30% from 36.21 bps on 12th March to 35.74bps on 23rd March 2020. However, the effective spread – which includes the cost of information asymmetry – increased from 9.50bps to 10.34bps.[5] This increase is due to the price impact (PI) component of the effective spread, which increased from -0.02 on 12th March to 0.01 on 23rd March, consistent with traders asking for higher prices because of the increased cost of adverse selection.

3.5.3 Baseline Model Results

Table 3.3 presents estimation results for the baseline model.

[4] We refer to the first Covid-19 lockdown as the time when the Thai government announced suspending Visa on Arrival (VOA) for nationals of 19 countries and cancelled visa exemptions for South Korea, Italy, and Hong Kong.

[5] The effective spread includes the cost of information asymmetry as it considers the impact of trading on the market prices. If there is information asymmetry, trading can reveal information to the market, leading to price movements. This impact is reflected in the effective spread, making it a more realistic measure of the actual cost of executing a trade.

Table 3.3: Panel Regression Analysis During the COVID-19 Pandemic on 12th and 23rd March 2020

	Dependent Variables										
Independent Variables	QS	ES	RS	PI	AMH	RT	RV	BV	JV	OI	PIN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel regression analysis: MWCB on 12th March 2020 (before the changed regulations of MWCB).											
Intercept	37.337****	9.731****	12.683****	-0.059**	9.970***	-0.00155****	0.00032****	0.730****	1.163****	74668.791***	0.692****
	(1.481)	(1.681)	(1.881)	(0.028)	(3.292)	(0.00013)	(0.00004)	(0.077)	(0.046)	(23219.277)	(0.011)
A dummy of post-	0.482	0.591	-4.007	0.092**	6.329***	0.00146****	0.0002****	0.447****	0.245****	-70100.007*	-0.028****
MWCB	(0.599)	(2.130)	(2.544)	(0.045)	(2.045)	(0.00022)	(0.00002)	(0.034)	(0.025)	(37484.901)	(0.003)
T	0.029*	-0.034	0.128*	-0.003***	0.333****	-0.00005****	0.000007****	0.018****	0.010****	2579.949**	-0.002****
	(0.017)	(0.060)	(0.072)	(0.001)	(0.058)	(0.000006)	(0.0000005)	(0.001)	(0.001)	(1055.738)	(0.0001)
T^2	-0.003****	0.001	0.003	-0.00004	0.005***	0.0000001	-0.00000002	0.00004	-0.0002****	-12.038	-0.00008****
	(0.001)	(0.002)	(0.002)	(0.00004)	(0.002)	(0.0000002)	(0.00000002)	(0.00003)	(0.00002)	(33.045)	(0.000003)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time(minute) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0110	0.0001	0.0008	0.0013	0.0506	0.0132	0.3252	0.4058	0.2967	0.0011	0.4816
Adj. R-squared	0.0105	-0.0004	0.0003	0.0008	0.0501	0.0128	0.3249	0.4055	0.2964	0.0006	0.4813
Observations	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000
Panel regression analysis: MWCB on 23rd March 2020 (after the changed Regulations of MWCB).											
Intercept	34.819****	11.405****	12.098****	-0.0143	9.011****	-0.00004	0.0001****	0.364****	0.897****	-3587.268	0.674****
	(1.643)	(1.808)	(1.834)	(0.0155)	(1.219)	(0.0001)	(0.00002)	(0.044)	(0.042)	(39186.460)	(0.012)
A dummy of post-	1.714****	-1.282	-2.492	0.0247	-1.718***	-0.0007****	0.00005***	0.019	0.108****	77159.569	0.014****
MWCB	(0.416)	(1.904)	(2.023)	(0.0249)	(0.622)	(0.0002)	(0.00002)	(0.019)	(0.022)	(61809.493)	(0.003)
T	-0.032***	0.151***	0.150***	-0.00006	0.049***	0.00001***	-0.000001**	0.001**	-0.004****	-305.184	-0.0004****
	(0.012)	(0.054)	(0.057)	(0.0007)	(0.018)	(0.000005)	(0.0000005)	(0.0005)	(0.0006)	(1751.242)	(0.00009)
T^2	-0.0002	0.002	0.002	-0.000003	0.0007	0.0000004***	0.00000004**	0.0001****	0.00008****	-13.939	-0.00004****
	(0.0004)	(0.002)	(0.002)	(0.00002)	(0.0006)	(0.0000001)	(0.00000002)	(0.00002)	(0.00002)	(54.953)	(0.000003)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time(minute) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0034	0.0037	0.0021	0.0006	0.0016	0.0057	0.0022	0.0183	0.0107	0.0009	0.0303
Adj. R-squared	0.0029	0.0032	0.0016	0.00009	0.0011	0.0052	0.0017	0.0178	0.0102	0.0004	0.0298
Observations	5943	5943	5943	5943	5943	5943	5943	5943	5943	5943	5943

Remarks: *p<0.10; **p<0.05; ***p<0.01; ****p<0.001; values in () stands for standard error.

These results show a notable difference between market quality immediately after the MWCBs on 12th March 2020 (“MWCB-1”) and 23rd March (“MWCB-3”). The price impact (PI) of MWCB-1 is 0.092 and significant, whereas the PI regression coefficient of MWCB-3 is insignificant. This indicates that traders executed trades away from their order prices after MWCB-1; however, there is no evidence of the same after MWCB-3. We attribute the difference in these responses to a learning effect. Traders unfamiliar with MWCBs leading up to MWCB-1 responded with panic orders, thereby reinforcing continued high market volatility. However, after sufficient time to reflect on the SET’s use of circuit breakers, by the time the third MWCB arrived, traders had gained some familiarity with MWCBs and learned to respond to trading halts without compromising the price at which they were willing to have their orders filled.

AMH illiquidity coefficients illustrate a similar learning effect. AMH illiquidity is significant and positive at 6.329 after MWCB-1, but significant and negative at -1.718 after MWCB-3, i.e., illiquidity increased after MWCB-1, but decreased after MWCB-3. This shows that whilst traders were still reluctant to enter the market after MWCB-1, there is no evidence of corresponding concerns immediately after MWCB-3; this interpretation is further corroborated by the order imbalance (OI) result, which is significant and negative after MWCB-1, but insignificant after MWCB-3. Indeed, the probability of informed trading (PIN), which captures the level of private information available to traders, is significant and positive at 0.014 after MWCB-3, but significant and negative after MWCB-1. This reversal in PIN shows that traders were significantly more informed in their trading responses to MWCB-3 than to MWCB-1, albeit their returns were lower after MWCB-3 (RT coefficient is -0.07%) than after MWCB-1 (RT coefficient is 0.146%) due to lower illiquidity.

Our results for price impact (PI), Amihud illiquidity (AMH), order imbalance (OI), and the probability of informed trading (PIN) evidence a learning effect created by MWCB-1 that conditioned the response of traders to MWCB-3 enabling the SET to curb market volatility where MWCB-1 had failed to do so. Realised volatility (RV) and jump variance (JV) were significant after each MWCB, but with considerably lower coefficients in MWCB-3: RV was 4.0 times lower (0.02% for MWCB-1 versus 0.005% for MWCB-3); JV was 2.3 times lower (0.245 for MWCB-1 versus 0.108 for MWCB-3). Consistent with the above, the bipower variance coefficient is significant after MWCB-1, but insignificant after MWCB-3.

Lastly, the quoted spread (QS) is insignificant after MWCB-1, but significant after MWCB-3. Consistent with Corwin and Lipson (2000), this shows that because traders were better informed after MWCB-3, bid-ask spreads were wider than after MWCB-1 as markets were still volatile.

3.5.4 DID Model Results

The DID model directly compares the impacts of each MWCB on market quality relative to each other. By construction, the individual impacts of each MWCB are unavailable. In this sense, the DID model is less informative than the baseline model. Nevertheless, with few exceptions, most of our DID results reinforce those of the baseline model and a learning effect evidenced by improved market quality after MWCB-3 relative to MWCB-1.

Table 3.4 presents results for the DID model.

Table 3.4: The Difference-in-Differences (DID) Regression Analysis

	Dependent Variables										
Independent Variables	QS	ES	RS	PI	AMH	RT	RV	BV	JV	OI	PIN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
The Difference-in-Differences (DID) regression analysis: comparison between after (23rd March 2020) and before (12th March 2020) the changes in regulations of MWCB.											
Intercept	36.359****	10.919****	12.940****	-0.041*	8.427****	-0.00109****	0.00025****	0.583****	1.010****	52687.726****	0.699****
	(1.514)	(1.798)	(1.914)	(0.021)	(1.183)	(0.00009)	(0.00003)	(0.064)	(0.046)	(14381.727)	(0.012)
Treat_s	-0.568	-0.714	-1.107	0.008	2.152*	0.00060****	-0.00003	-0.070	0.039	-34189.267****	-0.032***
	(1.016)	(1.306)	(1.424)	(0.015)	(1.192)	(0.000057)	(0.00003)	(0.073)	(0.055)	(8844.409)	(0.011)
$\mathrm{CB}_t^{\mathrm{POST}}$	1.416*	-2.266	-4.386**	0.043	10.763***	0.00046***	0.00034****	0.714****	0.470****	-25686.617	-0.057****
	(0.789)	(1.979)	(2.153)	(0.038)	(3.432)	(0.00015)	(0.00004)	(0.073)	(0.046)	(28068.129)	(0.008)
DID	-0.648	3.850**	2.233	0.031	-16.893***	-0.00015	-0.00042****	-0.955****	-0.589****	58076.917	0.102****
	(0.536)	(1.666)	(1.819)	(0.024)	(5.792)	(0.00011)	(0.00005)	(0.101)	(0.071)	(42621.479)	(0.011)
T	-0.001	0.058	0.140***	-0.002**	0.190**	-0.00002****	0.000003****	0.009****	0.003***	1147.259*	-0.0014****
	(0.018)	(0.047)	(0.049)	(0.001)	(0.086)	(0.000004)	(0.0000006)	(0.001)	(0.001)	(616.020)	(0.00019)
T^2	-0.002***	0.001	0.002	-0.00002	0.003	0.0000003***	0.00000001	0.00009	-0.00005	-12.634	-0.00006****
	(0.001)	(0.001)	(0.002)	(0.00002)	(0.002)	(0.0000001)	(0.00000003)	(0.00005)	(0.00005)	(13.114)	(0.000007)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time(day) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0063	0.0015	0.0013	0.0010	0.0436	0.0096	0.2022	0.3094	0.1723	0.0008	0.2269
Adj. R-squared	0.0059	0.0010	0.0008	0.0006	0.0432	0.0092	0.2019	0.3091	0.1720	0.0003	0.2266
Observations	11943	11943	11943	11943	11943	11943	11943	11943	11943	11943	11943

Remarks: *p<0.10; **p<0.05; ***p<0.01; ****p<0.001; values in () stands for standard error.

AMH illiquidity is significant at -16.893. Consistent with the baseline model, this shows that illiquidity reduced considerably immediately after MWCB-3 as traders returned to the market. The DID model also shows a significant and positive PIN result; the response of traders to MWCB-3 relative to MWCB-1 evidences a significantly higher probability of informed trading, consistent with the baseline model.

The third MWCB also significantly reduced volatility relative to MWCB-1. All measures of volatility, i.e., realised volatility (RV), bipower variance (BV), and jump variance (JV), are negative and significant.

Unlike the baseline model, DID results for the quoted spread (QS), returns (RT), and order imbalance (OI) are not significant. However, the effective spread (ES) is significant and positive at 3.850 in the DID model results (in the baseline model, ES is not significant). This result indicates significant buying pressure after MWCB-3 relative to MWCB-1 as the third circuit breaker restored market quality.

3.6 Conclusion

This paper finds evidence of learning effects in the repeated application of market-wide circuit breakers (MWCBs) in the Thai stock market in March 2020 at the time of the first Covid-19 lockdowns. Using baseline panel regression and DID models, our results show that after having experienced the first MWCB on 12th March, traders responded dissimilarly to the third MWCB on 23rd March – illiquidity and volatility reduced as traders transacted in higher volumes with significantly more private information. This learning effect is important; even though the first two MWCBs failed to curb volatility, the learning experience/familiarity they provided to traders conditioned a dissimilar and significantly better response to the third MWCB, thereby enabling the SET to restore normal market function. Our analysis is novel: as far as we know, prior studies of repeated MWCBs only evaluate their effects by analysing either single applications or a series of applications taken as a whole, i.e., in aggregate.

A consequence of learning effects we identify in this paper is their potential to reconcile divergent literature as to the effectiveness of MWCBs. To clarify, the first MWCB on 12th March 2020 in Thailand was ineffective at curbing extreme volatility. However, the third MWCB was effective. These opposing results are reconciled in our analysis by the conditioning of traders to respond dissimilarly to MWCBs by virtue of their recent experience of MWCBs. More generally, this implies that endogenising learning effects within the analysis of MWCB effectiveness may reconcile divergent results in the literature, whether the conditioning is a consequence of earlier MWCBs (as in our case), or due to other relevant information influencing how traders respond to a circuit breaker.

We make the following final remarks. First, it is possible that the use of MWCBs in other countries before/during March 2020 affected the response of traders to MWCBs in Thailand. For example, MWCBs in the US, Europe and other exchanges in South-East Asia during March 2020 may have influenced the response of traders to the third MWCB in Thailand. Since our estimations attribute learning to prior MWCBs in Thailand occurring in the first half of March 2020, learning effects generated by other information is an externality; we leave the matter of cross-border learning effects in MWCBs to further research. Second, whilst we identify learning effects in the particular sequence of MWCBs in Thailand, how important is their timing? For example, how long do traders need to digest the implications of a circuit breaker before it should be repeated if unsuccessful at the first attempt? Based on the time required to realise a learning effect, is there an optimal interval between MWCBs after which a further MWCB may be counter-productive?, e.g., because market quality is not restored, and the mechanism loses credibility. Each of these issues has a direct bearing on policies governing the use of MWCBs, and are left for further research. Finally, further research would be required to understand why the first MWCB failed to recover the market quality back to normal function and why the third restored the market quality efficiently.

Conclusion

Summary

This thesis provides significant contributions to the current body of literature through the execution of three empirical studies that tackle essential issues in the market microstructure field, using data from the Stock Exchange of Thailand (SET).

In the Thai stock market, foreign and domestic retail traders dominate the highest daily trading values. This is quite different from developed markets, where institutional investors are the most influential traders. Domestic retail traders pursue unique trading strategies, which may generate concerns in relation to their ability to respond efficiently to the escalated trading environment. Subsequently, their constrained ability to adapt to an increase in trading activity is expected to have a pronounced impact on stock prices. Generally, the price impact of escalating trading activity is low in highly liquid markets. Chapter 1 examines whether this relationship holds for the listed companies in the SET100 index, the most liquid stocks in the Thai stock market.

The aim of Chapter 1 is to explore the relationship between the price impact of trade and market returns and how turnover and market capitalisation affect this relationship. It uses vector autoregression (VAR), impulse response function (IRF), cumulative impulse response function (CIRF), and panel regression techniques to analyse data from 99 listed stocks in the SET100 index, spanning January to June 2019. The key findings of Chapter 1 can be summarised as follows. The results illustrate that entities listed in the SET100 index exhibit reduced information asymmetry, transaction costs, and heightened liquidity when compared to smaller-capitalisation ones listed outside the SET100 index. This phenomenon is attributed to the SET100 index encompassing the 100 largest listed firms in the Thai stock market. Additionally, the study reveals that the price impact of trades diminishes during favourable market conditions, such as a bullish market with a relatively high market capitalisation.

Furthermore, a positive correlation is observed between turnover and the bid-ask spread. The increased impact of trades on prices can be attributed to the inherent challenges faced by individual traders in managing high turnover and contributing to liquidity, as well as their difficulty in coping with the increased transaction volume, resulting in a decrease in market depth, reflected in the widening bid-ask spread.

Many findings suggest that in an order-driven market, traders' choice between limit and market order is influenced by market conditions (e.g. Biais et al., 1995; Handa and Schwartz, 1996; Foucault et al., 2005; Goettler et al., 2009). Traders also pursue different trading strategies with different levels of order aggressiveness in response to changes in market conditions (e.g. Duong et al., 2009; Chiu et al., 2017; Park et al., 2019). Therefore, Chapter 2 contributes to this investigation of the order submission aggressiveness of trader types in the Thai stock market: retail, foreign, and institutional traders. This chapter also examines how different types of traders adjust their order submission aggressiveness in response to market conditions, adopting an ordered logit regression methodology to analyse a sample of 100 listed stocks comprising the SET100 index from July to December 2019. The results indicate that the most strategic traders applying order submission aggressiveness are foreign traders who cancel their existing orders substantially, emphasising their sensitivity to non-execution risks. They trade faster than their counterparts and immediately cancel and resubmit orders to ensure they are matched. Their sensitivity to non-execution costs has also been discovered when the bid-ask spread widens and when there is reduced liquidity in the market. This suggests that they are cautious about the risks of being picked off when there is heightened volatility in the market, as reflected in their passive trading behaviour: either being absent from the market or submitting passive orders. Institutional traders adjust their order submission aggressiveness based on market conditions, especially volatility. They submit passive orders when selling stocks to manage the risk of being picked off. In contrast, they submit buying orders aggressively when the volatility increases, in order to profit from picking off stale limit orders, consistent with the findings of Duong et al. (2009). Retail participants trade slower than their counterparts, and their trading submission strategies are exposed to non-execution costs and picking off risk on both the buy and sell sides.

Finally, we investigate three consecutive activations of market-wide circuit breakers (MWCBs) that occurred in close succession in the Thai stock market in the month of March 2020 during the first COVID-19 lockdown. Such instances were infrequent. Moreover, the third activation of MWCB posed the risk of lost credibility if this failed to calm trading. To understand the effect of the amended MWCB regulations, it is important to analyse the ways in which traders in the Thai stock market adjusted in response to learning effects arising from earlier MWCBs. Thus, Chapter 3 investigates this phenomenon. We employ panel regression analysis and difference-in-differences (DID) estimation, using the pieces of all stocks of the SET100 index at a 1-minute trading horizon. In Particular, panel regression analysis and DID enable us to evaluate the impact of the first MWCB, which occurred on 12 March 2020, and the third MWCB, which occurred on 23 March 2020, on 11 different variables regarding market quality. These variables help capture changes in market conditions resulting from MWCBs by comparing the half-hour trading periods surrounding the triggering of the MWCBs.

The results show that the first MWCB was ineffective at restoring market quality. However, the third MWCB effectively enabled the stock exchange to restore normal market function, by curbing the heightened volatility. These results imply that even though the first MWCB was ineffective, it induced learning effects in the traders and, hence, resulted in a dissimilar response in the third MWCB, eventually allowing the SET to restore market quality. Thus, these learning effects help answer the question of the individual effectiveness of MWCBs when triggered sequentially. These findings also suggest that the literature on the effectiveness of MWCBs should include learning effects as endogenous factors, since the previous experience of traders during earlier MWCBs is likely to determine their trading behaviours in response to future circuit breakers.

Future Research

Following up on the findings of Chapter 1, it would be interesting to analyse all of the listed stocks in the SET100 index to see if they have high information asymmetry, for example, during the period before the earnings announcement. Regarding Chapter 2, it would be informative to compare the order submission aggressiveness of each type of trader in the listed stocks inside the SET100 index with those in, for example, the SETESG index, which includes 120 listed stocks, demonstrating sustainable business practices that consider the environment, social and governance (ESG) aspect (SET, 2024b). Concerning Chapter 3, a convincing approach would be to include crucial events arising simultaneously with repeated market-wide circuit breakers (MWCBs), e.g., the revision of short selling and limit up-limit down (LULD) restrictions. Also, in this analysis, we could categorise types of trader: retail, foreign, and institutional, to see how they responded to the sequential MWCBs and perhaps other revised SET regulations during the first COVID-19 lockdown in March 2020.

Appendix A

Appendix to Chapter 1

Table A.1: List of Stocks in SET100 Index in the Sample in the First Half of 2019

No.	Stock Symbol	Sector	No.	Stock Symbol	Sector
1	AAV	Transportation & Logistics	51	KCE	Electronic Components
2	ADVANC	Information & Communication Technology	52	KKP	Banking
3	AEONTS	Finance & Securities	53	KTB	Banking
4	AMATA	Property Development	54	KTC	Finance & Securities
5	ANAN	Property Development	55	LH	Property Development
6	AOT	Transportation & Logistics	56	MAJOR	Media & Publishing
7	AP	Property Development	57	MBK	Property Development
8	BANPU	Energy & Utilities	58	MEGA	Commerce
9	BBL	Banking	59	MINT	Food & Beverage
10	BCH	Health Care Services	60	MTC	Finance & Securities
11	BCP	Energy & Utilities	61	ORI	Property Development
12	BCPG	Energy & Utilities	62	PLANB	Media & Publishing
13	BDMS	Health Care Services	63	PRM	Transportation & Logistics
14	BEAUTY	Commerce	64	PSH	Property Development
15	BEC	Media & Publishing	65	PSL	Transportation & Logistics
16	BEM	Transportation & Logistics	66	PTG	Energy & Utilities
17	BGRIM	Energy & Utilities	67	PTT	Energy & Utilities
18	BH	Health Care Services	68	PTTEP	Energy & Utilities
19	BJC	Commerce	69	PTTGC	Petrochemicals & Chemicals
20	BLAND	Property Development	70	QH	Property Development
21	BPP	Energy & Utilities	71	RATCH	Energy & Utilities
22	BTS	Transportation & Logistics	72	ROBINS	Commerce
23	CBG	Food & Beverage	73	RS	Media & Publishing
24	CENTEL	Tourism & Leisure	74	SAWAD	Finance & Securities
25	CHG	Health Care Services	75	SCB	Banking
26	CK	Construction Services	76	SCC	Construction Materials
27	CKP	Energy & Utilities	77	SGP	Energy & Utilities
28	COM7	Commerce	78	SIRI	Property Development
29	CPALL	Commerce	79	SPALI	Property Development
30	CPF	Food & Beverage	80	SPRC	Energy & Utilities
31	CPN	Property Development	81	STA	Agribusiness
32	DELTA	Electronic Components	82	STEC	Construction Services
33	DTAC	Information & Communication Technology	83	SUPER	Energy & Utilities
34	EA	Energy & Utilities	84	TASCO	Construction Materials
35	EGCO	Energy & Utilities	85	TCAP	Banking
36	EPG	Construction Materials	86	THAI	Transportation & Logistics
37	ERW	Tourism & Leisure	87	THANI	Finance & Securities
38	ESSO	Energy & Utilities	88	TISCO	Banking
39	GFPT	Agribusiness	89	TKN	Food & Beverage
40	GLOBAL	Commerce	90	TMB	Banking
41	GOLD	Property Development	91	TOA	Construction Materials
42	GPSC	Energy & Utilities	92	TOP	Energy & Utilities
43	GULF	Energy & Utilities	93	TPIPP	Energy & Utilities
44	GUNKUL	Energy & Utilities	94	TRUE	Information & Communication Technology
45	HANA	Electronic Components	95	TTW	Energy & Utilities
46	HMPRO	Commerce	96	TU	Food & Beverage
47	INTUCH	Information & Communication Technology	97	TVO	Food & Beverage
48	IRPC	Energy & Utilities	98	WHA	Property Development
49	IVL	Petrochemicals & Chemicals	99	WHAUP	Energy & Utilities
50	KBANK	Banking	100	WORK	Media & Publishing

Notes: BEC is excluded from the sample since the SET replaced it in the middle period of the sample instead of GLOW which has free float lower than 20%, and GLOW is also excluded from the sample as the SET withdrew from the list of the SET100 in the middle period of the sample. Therefore, there are 98 stocks in the sample.

Table A.2: List of Stocks with a Market Capitalisation in Quartiles from 1 to 4

Quartile	Stock Symbol	Meaning
4^{th}	ADVANC AOT BBL BDMS BEM BJC CPALL CPF CPN DTAC EA GULF INTUCH IVL KBANK KTB MINT PTT PTTEP PTTGC SCB SCC TOP TRUE	The largest market capitalisation
3^{rd}	BANPU BGRIM BH BPP BTS CBG DELTA EGCO GLOBAL GPSC HMPRO IRPC LH MTC PSH RATCH ROBINS SAWAD SPRC TCAP TISCO TMB TOA TPIPP TU	The second-largest market capitalisation
2^{nd}	AEONTS BCH BCP BCPG BLAND CENTEL CHG CK CKP EPG ESSO HANA KCE KKP KTC MBK PLANB PTG QH SPALI STEC THAI TTW WHA WHAUP	The third-largest market capitalisation
1^{st}	AAV AMATA ANAN AP BEAUTY COM7 ERW GFPT GOLD GUNKUL MAJOR MEGA ORI PRM PSL RS SGP SIRI STA SUPER TASCO THANI TKN TVO WORK	The fourth-largest market capitalisation

Appendix B

Appendix to Chapter 2

B.1 The Formula of the Model to Study Order Aggressiveness

$$y^{*j}_{i,t} = a^j + \sum_{i=1}^{5} b^j_i x^j_{i,t-1} + \gamma^j_0 D^j_I + \varphi^j_0 D^j_F$$

$$+D^j_F\left(\sum_{i=1}^{5} \varphi^j_i x^j_{i,t-1}\right) + D^j_I\left(\sum_{i=1}^{5} \gamma^j_i x^j_{i,t-1}\right) + \varepsilon^j_t \qquad \text{(B.1.1)}$$

where $y^{*j}_{i,t}$ = the extent of order aggressiveness ranked by five order choices from the greatest to the lowest order aggressiveness for two trade directions (j = buy or sell) of order submission in stock i at time t,

a^j = an intercept of the model,

$x^j_{i,t-1}$ = the five explanatory variables: (1) the depth on the same side of the incoming order (DSameVol), (2) the depth on the opposite side of the incoming order (DOppVol), (3) the quoted spread (Qspread), (4) the waiting time of order (Wtime), and (5) the price volatility (Pvolat) in stock i at time t,

D^j_F = a dummy variable that equals unity for traders who are foreign and submit their orders in stock i at time t,

D^j_I = a dummy variable that equals unity for traders who are institutional and submit their orders in stock i at time t,

ε^j_t = the residual, which is independent but not identically distributed

B.2 How to Calculate Each Variable of the Equation (B.1.1):

1. The depth on the same side of the incoming order (DSameVol) is generated from the number of pending shares divided by 10,000 at the best bid (offer) as the orders arrive at time t.
2. The depth on the opposite side of the incoming order (DOppVol) is generated from the number of pending shares divided by 10,000 on the opposite side of the best bid (offer) as the orders arrive at time t.
3. The quoted spread (Qspread) is the difference between the best bid price and the offer price as the traders submit their orders at time t.
4. The waiting time of order (Wtime) is proxied by the average time elapsed, generated from the subsequence of order arrivals in the most recent continuous three orders.
5. The price volatility (Pvolat) is the transitory return volatility and is calculated from the standard deviation of the midquote return between time $t-20$ to t. Actually, it is the standard deviation of the most recent 20 continuously compounded midquote (midpoint) returns. By following Tsay (2010), we can apply the following rule:

The midpoint or midquote, $M_{i,t}$, is defined as

$$M_{i,t} = \left[\frac{P_{i,t}^{A} + P_{i,t}^{B}}{2}\right] \qquad \text{(B.2.1)}$$

where $P_{i,t}^{A}$ = the best ask price in the limit order book for stock i at time t

$P_{i,t}^{B}$ = the best bid price in the limit order book for stock i at time t

The corresponding one-period simple net return or simple return is

$$R_{i,t-20,t} = \frac{M_{i,t}}{M_{i,t-20}} - 1 = \frac{M_{i,t} - M_{i,t-20}}{M_{i,t-20}} \qquad \text{(B.2.2)}$$

where $R_{i,t-20,t}$ = rate of midquote return from time $t-20$ to t.

The Continuously Compounded Return

The natural logarithm of the simple gross midquote return of an asset is called the continuously compounded midquote return or log midquote return:

$$r_{i,t-20,t} = ln\left(1 + R_{i,t-20,t}\right) = ln\,\frac{M_{i,t}}{M_{i,t-20}} = m_{i,t} - m_{i,t-20} \qquad \text{(B.2.3)}$$

where $m_{i,t} = ln\ (M_{i,t})$

Therefore, the price volatility (Pvolat) can be calculated as follows:

During time period $t-20$ to t, we can calculate the continuously compound midquote return from time $t-1$ to t, time $t-2$ to t, ….., and time $t-20$ to t. This will generate 20 values of the continuously compound midquote return and then find the mean midquote return (r_m) of these 20 past values of the continuously compound midquote return.

$$r_m = \frac{1}{20}\sum_{i=t-20}^{t} r_{i,t-i,t} \qquad \text{(B.2.4)}$$

After that, we can find the standard deviation (r_{sd}) of the continuously compound midquote return between time $t-20$ to t as follows:

$$r_{sd} = \sqrt{\frac{1}{19}\sum_{j=t-20}^{t}\left(r_{i,t-j,t} - r_m\right)^2} \qquad \text{(B.2.5)}$$

Appendix C

Appendix to Chapter 3

C.1 Variable Definitions

Table C.1: Market Quality Measures

Variables	Definition
Liquidity measures	
Quoted spread (QS_{it})	$QS_{it} = \left[\frac{\frac{p_{it}^{A} - p_{it}^{B}}{m_{it}}}{2}\right]$ p_{it}^{A} is the best ask price in the limit order book for stock i at time t, p_{it}^{B} is the best bid price in the limit order book for stock i at time t, m_{it} is the midpoint price for stock i at time t.
Effective spread (ES_{it})	$ES_{it} = \left[d_{it} \times \left(\frac{p_{it}^{E} - m_{it}}{m_{it}}\right)\right]$ d_{it} is the trade direction indicator, i.e., +1 if a buy order and -1 if a sell order. p_{it}^{E} is the execution price in the limit order book for stock i at time t.
Realised spread (RS_{it})	$RS_{it} = \left[d_{it} \times \left(\frac{p_{it}^{E} - m_{it+x}}{m_{it}}\right)\right]$ m_{it+x} = the midpoint price one minute after the trade where $x = 1$

Table C.1: Market Quality Measures (Continued)

Variables	Definition
Liquidity measures	
Price impact (PI_{it})	$PI_{it} = 2 \times d_{it} \times [\ln(P^{mid}_{it-x}) - \ln(P^{mid}_{it})] \times 100$ $\ln(P^{mid}_{it})$ is the logarithmic value of the mid-point price of stock i on time t $\ln(P^{mid}_{it-x})$ is the logarithmic value of the mid-point price of stock i before time t (at time t-x where x = 1)
Amihud (AMH_{it})	$AMH_{it} = \left(\frac{1}{N} \times \sum_{k=t-N+1}^{t} \frac{\lvert r_{ik} \rvert}{P_{ik}V_{ik}}\right) \times 1{,}000{,}000$ N = 30 (look-back window size). r_{ik} = The return of stock i at time k. P_{ik} = The price of stock i at time k. V_{ik} = The volume of stock i at time k.
Return measure	
Return (r_{it})	$r_{it} = \ln(P^{mid}_{it}) - \ln(P^{mid}_{it-x})$
Volatility measures	
Realised variance (RV_{it})	$RV_{it} = \sum_{t=1}^{30} r^2_{it}$
Bipower variation (BV_{it})	$BV_{it} = \frac{1}{2} \times \pi \times \sum_{t=2}^{30} (\lvert r_{it} \rvert \times \lvert r_{it-1} \rvert)$
Jump variation (JV_{it})	$JV_{it} = \max(RV_{it} - BV_{it}, 0)$[1]

[1] JV_{it} is truncated at zero. Results for BV_{it} and JV_{it} are reported as a percentage value with the square root multiplied by 100, i.e., as $\sqrt{BV_{it}} \times 100$ and $\sqrt{JV_{it}} \times 100$.

Table C.1: Market Quality Measures (Continued)

Variables	Definition
Volatility measures	
Order Imbalance (OI_{it})	$OI_{it} = Depth_{it}^{best\ ask} - Depth_{it}^{best\ bid}$ $Depth_{it}^{best\ ask}$ is depth of the best ask price of stock i at time t. $Depth_{it}^{best\ bid}$ is depth of the best bid price of stock i at time t
Informed trading measure	
Volume-synchronised probability of informed trading (PIN_{it})	$PIN_{it} = \frac{1}{N} \times \sum_{k=t-N+1}^{t} \frac{\lvert V_{ik}^{S} - V_{ik}^{B} \rvert}{V_{ik}}$ $V_{ik}^{B} = V_{ik} \times Z \times \left(\frac{\Delta P_{ik}}{\sigma \Delta P_{ik}}\right), V_{ik}^{S} = V_{ik} - V_{ik}^{B}$ N = 30 (look-back window size in minutes).

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