THE IMPACT OF ALGORITHMIC TRADING ON THE MARKET QUALITY IN THE STOCK EXCHANGE OF THAILAND

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A Dissertation Submitted in Partial
Fulfillment of the Requirements for the Degree of
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ABSTRACT

Title of Dissertation	The Impact of Algorithmic Trading on the Market Quality in the Stock Exchange of Thailand
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This dissertation aims to study how the rising algorithmic trading activities in the Stock Exchange of Thailand affects the market quality. I conducted three researches to investigate the impact of algorithmic trading. One is on the impact of algorithmic trading on volatility. Second is on the effect of algorithmic trading on liquidity and third is on the relationship between algorithmic trading and price efficiency. Furthermore, I introduced two new algorithmic trading proxies, namely, algorithmic trading initiated by institutional and foreign investors to investigate the effect of algorithmic trading initiated by these two investors on the market quality.

The first research demonstrates how algorithmic trading affects stock volatility in the Stock Exchange of Thailand. The study is based on SET100 stocks from March to December 2016. I implemented the OLS regression to establish the relationship between algorithmic trading and volatility and the two-stage least square regression and the Granger causality test to verify the causal relationship. I showed that on average, algorithmic trading proxy is associated and has a causal relationship with negative volatility. However, individually, algorithmic trading proxy is related to positive volatility. Similarly, algorithmic trading initiated by institutional and foreign investors lower realized and range-based volatility. During the volatile period, algorithmic trading decreases range-based volatility. There is no evidence that algorithmic trading affects realized volatility in the volatile period.

The second research investigates the relationship between algorithmic trading and liquidity. In general, I found that algorithmic trading deteriorates liquidity by widening effective spread and lowering share turnover in the short run and reducing liquidity ratio in the long run. I confirmed the result by using the two-stage least square and showed that algorithmic trading causes liquidity to decrease by enlarging effective spread and shrinking share turnover. Information asymmetry is used to explain this phenomenon. An increase in algorithmic trading imposes adverse selection cost onto other investors, causing them to decrease their participation. Algorithmic trading initiated by foreign investors has more profound effect on deteriorating short-run liquidity while algorithmic trading initiated by institutional has more profound effect on decreasing long-run liquidity. During the volatile period, algorithmic trading also associates with lowering liquidity for all measures. The slope coefficient of algorithmic trading during volatile period is higher than during the whole sample except for the share turnover. Therefore, algorithmic traders have less effect on lowering share turnover during the volatile period than during the entire period.

The third research determines whether the rise of algorithmic trading enhances price efficiency. There is no evidence that algorithmic trading influences price efficiency. However, when probing further, I found that algorithmic trading initiated by institutional and foreign investors and their interaction terms decrease pricing error, facilitating price efficiency. Furthermore, algorithmic trading initiated by foreign investors has a larger effect on augmenting price efficiency. During the volatile period, algorithmic trading, on the contrary, decreases price efficiency and enlarges price errors.

Finally, this dissertation investigates the effect of algorithmic trading on market quality in detail and provides insightful conclusion for policymakers, regulators and investors in order to regulate or react to the increase in algorithmic trading strategies in the Stock Exchange of Thailand.

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Pavinee Hassavayukul

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TABLE OF CONTENTS

LIST OF TABLES

Tables **Page**

LIST OF FIGURES

Figures **Page**

ABBREVIATIONS

Abbreviations	Equivalence
2SLS	Two-stage least squares
ARCH	Autoregressive Conditional Heteroskedastic
ARMA	Auto regressive moving average
AT	Algorithmic trading
CAPM	Capital asset pricing model
DMA	Direct market access
FE	Fixed-effect estimator
GARCH	Generalized autoregressive conditional heteroskedasticity
GMM	Generalized method of moments
HFT	High frequency trading
IPO	Initial public offering
IV	Instrumental variable
OLS	Ordinary least square
RBV	Range-based volatility
REM	Random effects model
RV	Realized volatility
SET	Stock exchange of Thailand
SUR	Seemingly unrelated regression
VAR	Vector autoregression
VIF	Variance inflation factor
VMA	Vector moving average

CHAPTER 1

INTRODUCTION

Algorithmic trading (AT) is the trading which is executed by computer algorithms to take certain positions in response to market information. Algorithmic traders utilize mathematical models, fast network system and automated program. They use historical data to determine their trading strategies and backtest their algorithms to verify their correctness and performance (Chan, 2009). When the strategies are executed, the trading programs gather market information, process the acquired information and decide the trading securities, the positions, the order types, the volume and the prices. Finally, the algorithms submit the orders automatically without any human interference. The orders may be sent to various trading venues in order to execute the orders via the best venues. Examples of the venues are: direct market access (DMA), electronic communication network (ECN), dark pools and multiple execution venues. While sending their orders, they also use computer programs to implement real-time risk management. Figure 1.1 illustrates the process. Algorithmic trading is present in all financial assets: equity, commodities, currency and futures.

Figure 1.1 The Process of Algorithmic Trading

Algorithmic trading employs many different strategies. Figure 1.2 categorizes the type of the algorithmic traders. Algorithms can be as simple as using computer programs to avoid price impact; or they can be as sophisticated as using artificial intelligence to trade stocks. High frequency trading is a subset of algorithmic trading.

It engages in an ultrafast trading. The latency for the high frequency arbitragers is less than 100 milliseconds (Scholtus, van Dijk, & Frijns, 2014).

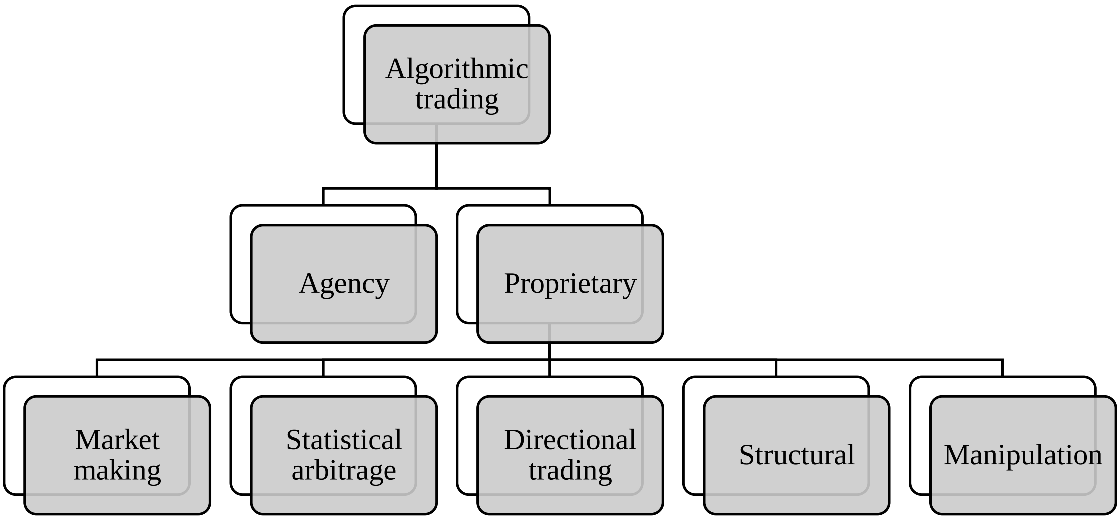

Figure 1.2 Types of Algorithmic Trading

The Securities and Exchange Commission (SEC & CFTC, 2010) defined high frequency traders with the following characteristics: 1) use of high-speed algorithms, 2) use of co-location, 3) very short latency, 4) fleeting orders and 5) net zero position at the end of the day. The main characteristic of algorithmic trading is its speed or latency. Hasbrouck and Saar (2013) defined latency as the time delays in which traders react to the new information. Riordan and Storkenmaier (2012) defined latency as the time taken between the submission and feedback of the orders. As market becomes more complex, more information is available. Speed is important for the profitability of the investors. The typical latency ranges from 50 to 150 milliseconds whereas the fastest high frequency traders can achieve five millisecond latency (Scholtus & van Dijk, 2012). With this speed, human traders cannot compete with algorithmic traders.

As a result, hedge funds and broker dealers implement high frequency trading by using the fastest algorithms and locating their computers at the nearest locations to the trading venues in order to reduce latency and outperform their competitors (Hasbrouck & Saar, 2013). Brogaard, Hendershott, and Riordan (2014) proposed that high frequency trading starts to replace the task of market makers. They utilize the law of large numbers-they trade a lot of transactions at a high frequency and an ultra-high speed. The speed of trading is in the matter of milliseconds. The difference between market makers and high frequency traders are the privileged access to the markets. Market makers have the privileged access to the market, but they also have obligations to be the liquidity suppliers because they have access to better information about the market; whereas, high frequency traders can be both liquidity suppliers and liquidity demands. Thusly, they can profit by either buying low and selling high; or locating where the large orders are and filling these orders.

Researchers categorize algorithmic trading strategies into two main groups, namely, agency and proprietary algorithms (Hagströmer & Nordén, 2013; Hasbrouck & Saar, 2013; Menkveld, 2014). Agency algorithms are used to minimize execution costs by slicing large orders into smaller orders. This enables institutional investors such as pension funds, brokers and mutual funds, to mitigate market impact, reduce transaction cost and control volatility risk in order to achieve optimal executions (Almgren & Chriss, 2001; Biais & Foucault, 2014).

Another type of algorithmic trader is the proprietary algorithm. Trades of proprietary algorithms often involve in shorter holding period than the ones of agency algorithms. Proprietary algorithms aim to profit from the trades. High-frequency trading is a subset of proprietary algorithms. There are two types of proprietary algorithms: market-making and opportunistic trading. The market-making algorithmic traders offer the best bids and asks in the limit order book and hence provide liquidity when needed. Their profits are from the bid-ask spread. They are different from the traditional market makers because their roles in providing liquidity are not mandatory.

Opportunistic algorithmic traders implement statistical arbitrage, directional trading, structural and manipulation strategies (Aldridge, 2013; Biais & Foucault, 2014). Statistical arbitragers use their fast market access to search for arbitrage opportunities, which is the deviations in the prices of paired or related assets. They use high frequency trading and market orders to exploit these opportunities. Directional strategies gather market information such as index future prices (Jovanovic & Menkveld, 2016), news announcement, limit order book updates and market-wide returns (Brogaard, Hendershott, & Riordan, 2014) to predict future price movements. Then, they place the directional bet. Structural strategies take advantage of certain market structure. The example of this type of strategies are cross-quote in a fragmented market, co-location etc. Manipulation strategies use their fast market access to involve in market manipulation. The strategies are momentum ignition strategies, smoking, spoofing, quote stuffing etc.

Financial institutions face numbers of challenges such as market complexity, risks, high competition, regulation and low trading volume. Financial institutions and investors adopt various types of technology to overcome these challenges. One of the technological advancements is algorithm trading. Kirilenko and Lo (2013) explained that the factors which facilitate algorithmic trading are financial complexity, quantitative modeling and technological advancement. The complexity of the stock markets is due to an increasing number of market participants, various types of financial instruments and large flow of data. Algorithms provide the investors the instruments to retrieve and analyze incoming information more effectively. Furthermore, the quantitative models such as Markowitz's portfolio theory, Sharpe's capital asset pricing model, Rosenberg's linear multifactor risk model and Black-Scholes' option-pricing model, enable computer programs to make trade decisions. Algorithms can easily execute the strategies such as passive investment, arbitrage trading, automated execution, market making and high frequency trading, thus, enabling algorithmic trading to increase in quantity.

Therefore, financial institutions and investors use algorithmic trading to improve efficiency, reduce cost, possess competitive advantages, eliminate human errors, foster productivity and manage risks (Hammer, 2013; Kirilenko & Lo, 2013). The transaction cost is reduced due to its large trading volume and the reduced opportunity cost of monitoring the market. Furthermore, as computer algorithms can monitor the market information and execute the orders with lightning speed, these abilities generate more trading opportunities. Algorithmic traders execute orders according to pre-programmed and tested algorithms. Therefore, this reduces the amount of errors, which are typically occurred using manual entries. More importantly, the use of algorithmic trading technology eliminates human emotion, which is normally associated with irrational decisions and psychological biases.

Algorithmic trading has become a significant market participant, in term of both trading volume and the number of trades, in many exchanges. In 2018, 80% of all trades in the U.S. were generated by algorithms (Amaro, 2018). At its peak, high frequency trading was accounted for 70% of all trading in the US stocks. In 2017, algorithmic trading generated about 60% of the trading in the U.S. (Cheng, 2017) whereas in Europe, 40% of all trading volumes were algorithmic (QY Research Group, 2018). In Thailand, program trading (one of the services for algorithmic traders provided by SET) was accounted for 3% of trading volume and 13.25% of number of trades (Likitapiwat, 2016). In 2015, the combined trading volume via direct market access (DMA) and program trading accounted for 14% of trading volume (Stock Exchange of Thailand, 2015). I believe that the number at the moment is around 20% although the exact number is not known due to the proprietary nature of the intraday data.

The increasing dominance of algorithmic trading alters market microstructure because it causes the number of fleeting orders to increase. Fleeting orders are the limit orders which are cancelled within a short period after the order submission. Hasbrouck and Saar (2009) investigated one hundred stocks listed in NASDAQ and found that within two seconds, 33% of limit orders got cancelled. Viljoen, Westerholm, Zheng, and Gerace (2015) provided the evidence that the algorithmic traders in the Austrian Stock Exchange used the fleeting orders to search for market liquidity.

Another characteristic of the algorithmic trading is that human has a little or no involvement with trading executions. Though this may eliminate emotions and biases from the trading decisions, without human interference, the trading may have errors and can result in a huge loss as witnessed in the case of Knight Capital who lost 440 million US dollar in the wake of faulty test of trading software.

Algorithmic trading has many drawbacks. One is its complexity. The interactions among computer software, various type of human traders, financial instruments and systems are very complex to conceptualize and model. Second, as algorithmic traders possess information with higher speed and obtain faster market access, they might profit on the expense of other traders, rising the questions about fairness and the need for regulations.

Furthermore, many researchers concern that algorithmic trading is the source of market instability due to the increasing frequency of the incidents which might be related to algorithmic trading. They are the Quant meltdown of August 2007, the Flash crash of May 6, 2010, the Facebook IPO of May 18, 2012, the Flash crash of British pound of October 7, 2016, the Flash crash of Ethereum of June 22, 2017 and many more. These events often result in billions of dollar loss, a massive decline in prices and in some case, the rapid rebound of the prices within a few hours and finally lawsuits. For example, the Flash crash of May 6, 2010, which was triggered by the implementation of spoofing algorithms by a trader in London named Navinder Singh Sarao, resulted in trillion dollars loss, 9% drop in S&P 500 and 1,010 points drop in the Dow Jones Industrial Average. The aftermath of this incident led to an introduction of the individual stock circuit breakers and the regulation of the direct access. The flash crash in pound sterling caused pound sterling to drop by 9%. Furthermore, recently, in the stock market of Thailand, a mini flash crash for AOT on October 15, 2016 where its price dropped from 350 baht to 300 baht within one second and regained its value within a few second was documented.

Given both benefits and detriments of algorithmic trading, the rise of algorithmic trading has puzzled researchers on its impact on market quality. This question is of interest to the regulators. If algorithmic traders exert negative externalities on other investors, there might be the need for regulation. For example, the Securities and Exchange Board of India proposed to implement the minimum resting time mechanism which do not allow traders to update or cancel the orders before 500 milliseconds after the receipt of the orders due to the increasing numbers of fleeting orders (Securities and Exchange Board of India, 2016).

McMillian, Pinto, Pirie, and van de Venter (2011) listed the functions of the financial systems: 1) to facilitate the achievement of the goals of traders, 2) to enable price discovery process and 3) to allocate capital to its best uses. Harris (2003) defined efficient market by the following terms: liquidity, transaction costs, informative prices, volatility and trading profits. High quality market is essential for the economic growth. The regulator needs to ensure that the markets are efficient and fair for all traders. Information and liquidity are motives for trading. The efficient market hypothesis suggests that market prices fully reflect all available information and should follow a random walk (Fama, 1970). This assumes that the market is frictionless, information is complete, underlying asset is liquid and investors are rational and optimize their utility functions. Foucault, Pagano, and Roell (2013) stated that the conditions for the efficient market hypothesis to hold is that "all potential participants are present on the market;

these participants convey to the market orders that reflect their demands or supply of securities, and they are not affected by actions of other market participants; an auctioneer balances the quantities demanded and supplied at a single equilibrium price that reflects a consensus view of the security's 'fundamental value'".

In reality, there are various degree of frictions preventing the efficient prices to take place and reducing liquidity. First, all potential participants are not present on the market at all time. Second, there are information asymmetry among traders; thus, some traders may infer their information from the behaviors of other traders. Third, the market is not always at equilibrium. Grossman and Stiglitz (1980) suggested that the idea that it is impossible for the market are always efficient. This is because it is costly to obtain information, informed investors, therefore, need to be compensated. Thus, if prices are always efficient, then there cannot be a compensation for the investors. Black (1986) characterized investors into informed and noise traders. Informed investors are the investors who obtain and submit their orders according to their information about fundamentals. Noise traders, on the other hand, infer information from prices and quotes. Admati and Pfleiderer (1988) categorized investors into two types according to their motives: informed investors and liquidity traders. Similar to Black (1986), informed investors are the investors who trade based on their private information. On the contrary, liquidity traders trade for other reasons besides firm's fundamental values. They are, for example large, institutional investors who trade on the behalf of their clients or to perform portfolio-balancing. The behavior of the market, therefore, depends on the interaction between groups of traders (Harris, 2003).

An increase in algorithmic trading also raises concerns among practitioners. Upon closing Jabre Capital Partners SA, Phillippe Jabre wrote in his letter to investors that "financial markets have significantly evolved over the last decade driven by new technologies and the market itself is becoming more difficult to anticipate as traditional participants are imperceptibly replaced by computerized models" (Horta e Costa & Hu, 2018). Algorithmic trading is often blamed for increased risk and withdrawn liquidity during market distress. In response to the Flash Crash of May 6th, 2010, BlackRock published the white paper, stating that "The lesson of the event [the Flash Crash] was clear from the beginning: better rules are needed to help protect investors, and to reflect the tremendous evolution that has occurred in the markets in recent years. What has happened since the Flash Crash to reform markets to reduce the risk of another?" (BlackRock, 2011). This also emphasizes in the report by Charles Himmelberg, a co-head of global market research at Goldman Sachs. He wrote that "One theory that has been proposed for why market fragility could be higher today is that because HFTs [high-frequency trading] supply liquidity without taking into account fundamental information, they are forced to withdraw liquidity during periods of market stress to avoid being adversely selected… In our view, this at least raises the risk …. the inability of the market's liquidity providers to process complex information may lead to surprisingly large drops in liquidity when the next crisis hits," (Kim, 2018).

Due to its implication to regulators and practitioners, an increasing number of researches are conducted to investigate the effect of algorithmic trading on market quality and market stability such as Brogaard (2011), Brogaard, Hendershott, and Riordan (2014), Hendershott, Jones, and Menkveld (2011), Biais, Foucoult, and Moinas (2015), Brogaard, Henershott, Hunt, Latza, Pedace, and Ysusu (2012), Foucault, Hombert, and Rosu (2016), Malinova, Parks, and Riordan (2018), Chaboud, Chiquoine, Hjalmarsson and Vega (2014), Boehmer, Fong, and Wu (2015) and etc.

In the Stock Exchange of Thailand, the number of algorithmic trading is increasing. Therefore, it is interesting to investigate the impact of algorithmic trading on market quality. This is useful for policymakers such as the Securities and Exchange Commission, Thailand (SEC) and the Stock Exchange of Thailand (SET). However, the research on the topic of the effect of algorithmic trading on market quality in an emerging market is limited. Furthermore, an emerging market has a unique feature in which the type of investors plays a different role in term of price impact (Richards, 2005), information advantage (Dvořák, 2005) and trading behaviour and performance (Phansatan, Powell, Tanthanongsakkun, & Treepongkaruna, 2012). By incorporating the type of investors into the algorithmic trading measurement, I can investigate how the use of technological advancement affects the characteristics of the institutional and foreign investors. In this thesis, I investigated in detail the effect of algorithmic trading on market quality.

1.1 Research Objectives

This thesis focuses on the analysis of the impact of algorithmic trading on three dimensions of interrelated market quality, namely, volatility, liquidity and price efficiency in the Stock Exchange of Thailand. Furthermore, we introduced a new measurement to measure the algorithmic trading initiated by institutional investors proxy and the algorithmic trading initiated by foreign investors proxy to understand their effects on market quality. Therefore, the primary objectives of this paper are:

1) To understand the effect of algorithmic trading on volatility, liquidity and price efficiency.

2) To investigate the causal relationship between algorithmic trading and volatility, liquidity and price efficiency.

3) To find out the effect of algorithmic trading on volatility, liquidity and price efficiency during the volatile market.

4) To establish the effect of algorithmic trading initiated by institutional investors on volatility, liquidity and price efficiency.

5) To determine the effect of algorithmic trading initiated by foreign investors on volatility, liquidity and price efficiency.

6) To examine the effect of algorithmic trading initiated by institutional investors on volatility, liquidity and price efficiency during the volatile period.

7) To study the effect of algorithmic trading initiated by foreign investors on volatility, liquidity and price efficiency during the volatile period.

1.2 Contributions of the Research

The primary aim of this thesis is to research the effect of algorithmic trading on the market quality, namely, volatility, liquidity and price discovery, in the Stock Exchange of Thailand. So far, most studies focus on the effect of algorithmic trading on developed markets and concern only the effects of aggregate algorithmic trading. This thesis contributes to the market microstructure and financial economics fields. First, this study demonstrates how AT affects market quality in an emerging market.

Second, to the best of my knowledge, this is the first study to introduce the method of identifying AT proxies associated to each types of investors and examine their effects on market quality. Finally, it provides the evidence to the policy debates on whether there should be regulations on algorithmic trading or not

The effects of AT on market quality affect both investors' welfare and cost of capital for companies because illiquidity represents costs to all types of investors. By holding less liquid stocks, investors require higher return which eventually leads to an increase in the cost of capital for firms and their stock values. In the first essay, I demonstrate that algorithmic trading is negatively related to price volatility and cause the price volatility to change. In the second essay, I showed that the increase in algorithmic trading deteriorates liquidity and presented the causal relationship using the instrumental variable. Finally, in the third essay, along with two previous results, I demonstrate that algorithmic trading initiated by institutional and foreign investors are associated with a decline in price efficiency. All in all, I present the effect and the causal relationship between algorithmic trading (as a whole and separated by the type of investors who initiated the trade) and market quality.

1.3 Research Outline

The following is the outline of this thesis. In Chapter 2, I present the overview of the Stock Exchange of Thailand and describe our data. In Chapter 3, I examine the effect of algorithmic trading on volatility. In Chapter 4, I demonstrate the effect of algorithmic trading on liquidity and introduce the instrumental variable to verify the causal relationship. Furthermore, the algorithmic trading initiated by each type of investors proxies are introduced and are used to examine how the algorithmic trading initiated by each type of investors affect liquidity. In Chapter 5, I determine the impact of algorithmic trading and price efficiency. Finally, I conclude in Chapter 6.

CHAPTER 2

THE STOCK EXCHANGE OF THAILAND

All results presented in this thesis are based on the analysis of the SET100 stocks listed in the Stock Exchange of Thailand. The intraday order and deal data were obtained from the Stock Exchange of Thailand database. I used this data to perform the analysis of the effect of algorithmic trading on market quality. In this chapter, I introduced the overview of the Stock Exchange of Thailand.

2.1 SET Trading System and Period

The Stock Exchange of Thailand (SET) is a fully computerized trading and has the continuous order-driven trading and auction systems. SET has implemented a fully computerized trading system since April 1991 and in August 2008, it has implemented "Advance Resilience Matching System" (ARMS). By September 2012, SET used the securities trading system called "SET CONNECT" which speeds up transaction and improves international market access.

The trading hour is between 9.30 and 17.00, with eight trading session: Pre-opening I, Morning Trading Session, Intermission, Pre-opening II, Afternoon Trading Session, Pre-close, Off-Hour Trading and Market Close. Pre-Opening I starts at 9.30 to time T1 which is the time between 9.55 and 10.00 randomized for the opening trading time while Pre-Openings II starts at 14.00 to time T2 which is the time between 14.25 and 14.30 randomized for the opening trade time. For the opening prices, they use the auction method. Following the opening time is the morning and the afternoon trading sessions which run from T1 to 12.30 and T2 to 16.30 respectively.

The trading methods are automatic order matching (AOM) and trade report. AOM matches orders first by price and then by time. After receiving orders from the brokerage houses, SET CONNECT system queues them by prices and then by ordering time. So, orders are first arranged according to prices and the best price are priorized.

For each price group, orders are queued first-in-first-out. For the big lots, foreign buy-in, member buy-in and off hour, brokers may trade directly with each other. The actual trading prices may not be the same as their bid/ask prices. After deals are made, brokers report back to SET CONNECT system regarding their transactions. During the regular trading hour, SET CONNECT will match the orders according to the queuing system as described above and trade reports occur while during the pre-opening sections. Auction methods are used in order to prevent price manipulations and to stabilize opening prices. For the auction trading method, opening and closing prices are determined by using the prices that generate the highest executable volume. If there are multiple prices that fit the mentioned criteria, the system will open or close at the prices that have the greatest executable volume and the minimum imbalance. The exchange stops trading during the intermission period which lasts from 12.30 to 14.00. Pre-close is the period between 16.30 to T3 which is between 16.35 and 16.40. The closing prices are determined by the auction method. Next is the off-hour trading period from time T3 to 17.00 where only the trade report trading method is permitted. After 17.00, SET is closed.

In the Stock Exchange of Thailand, there is a limitation on the minimum price movement called tick size. Table 2.1 shows the tick sizes for each price level.

Table 2.1 Tick Sizes

Market Price Level (THB)	**Tick Size (THB)**
(0.00, 2.00)	0.01
(2.00, 5.00)	0.02
(5.00, 10.00)	0.05
(10.00, 25.00)	0.10
(25.00, 100.00)	0.25
(100.00, 200.00)	0.50
(200.00, 400.00)	1.00
400.00 up	2.00

2.2 SET Services

The Stock Exchange of Thailand (SET) has several services that support the implementation of algorithmic trading activities. They are: Direct market access, Program trading and Co-location services. Direct Market Access (DMA) enables eligible investors to place the orders directly to the broker's order management system which then routes the quotes in the SET trading system. Figure 2.1 illustrates the process. Program trading enables algorithmic traders or high frequency traders to generate orders automatically via their pre-programmed algorithms. This service is available for broker members. This helps algorithmic traders to grow in the Stock Exchange of Thailand. Furthermore, SET offers the co-location service which allow investors to install their servers at the SET data center. This helps to diminish the execution times. Therefore, the Stock of Exchange of Thailand is a good platform to study the impact of algorithmic trading on market quality. Figure 2.2 illustrates the process.

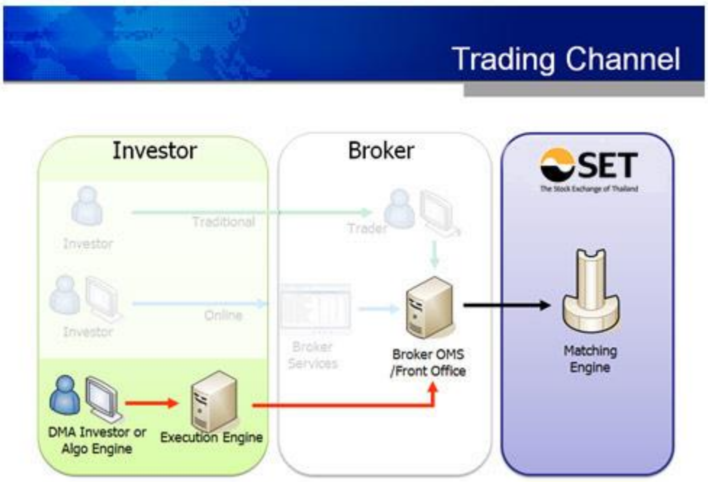

Figure 2.1 Direct Market Access (DMA) Channel
Source: Set Group, 2019a.

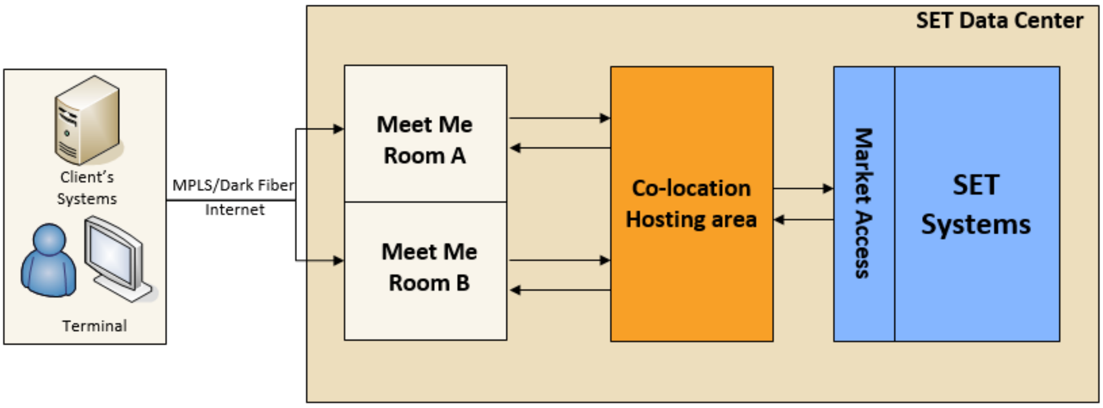

Figure 2.2 Co-location Channel

Source: Set Group, 2019b.

2.3 Data

I utilized a sample of algorithmic trading activities and market quality. The sampling period was from March to December 2016. During the sampled period, the SET index experienced an upward trend. The SET index was at 1,346.95 on March 1, 2016 and at 1,542.94 on December 30, 2016. The market return was 14.55% for 10 months. The highest SET index was 1,552.64 whereas the lowest SET index was 1,346.95. Figure 2.3 illustrates the SET index between March and December 2016.

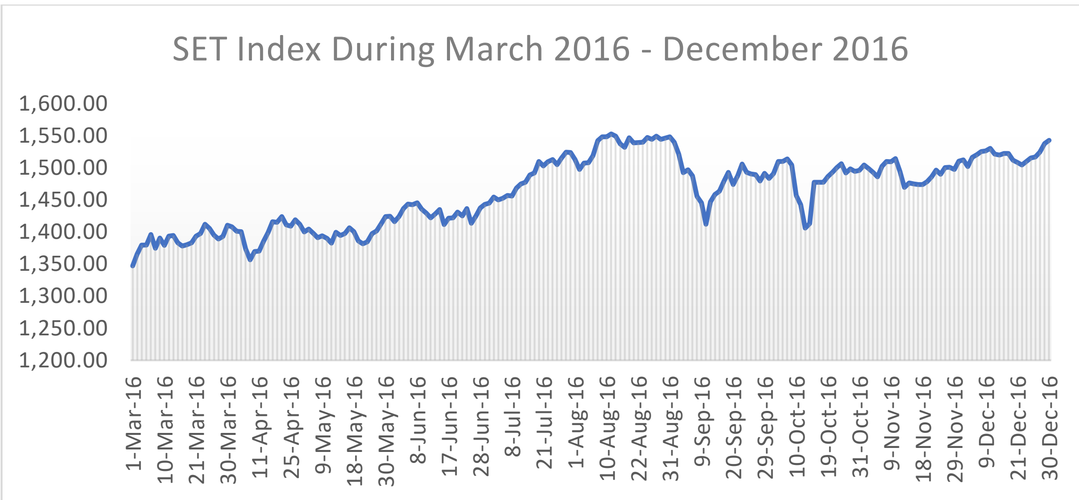

Figure 2.3 SET Index (March-December 2016)

The SET100 or the composite index for the top 100 stocks with the largest market capitalization was between 1,921.78 on March 1, 2016 and 2,178.19 on December 30, 2016, with the return of 13.34% for 10 months. For SET100 index, the highest value was 2,219.43 while the lowest value was 1,916.74. Table 2.4 illustrates the SET100 index.

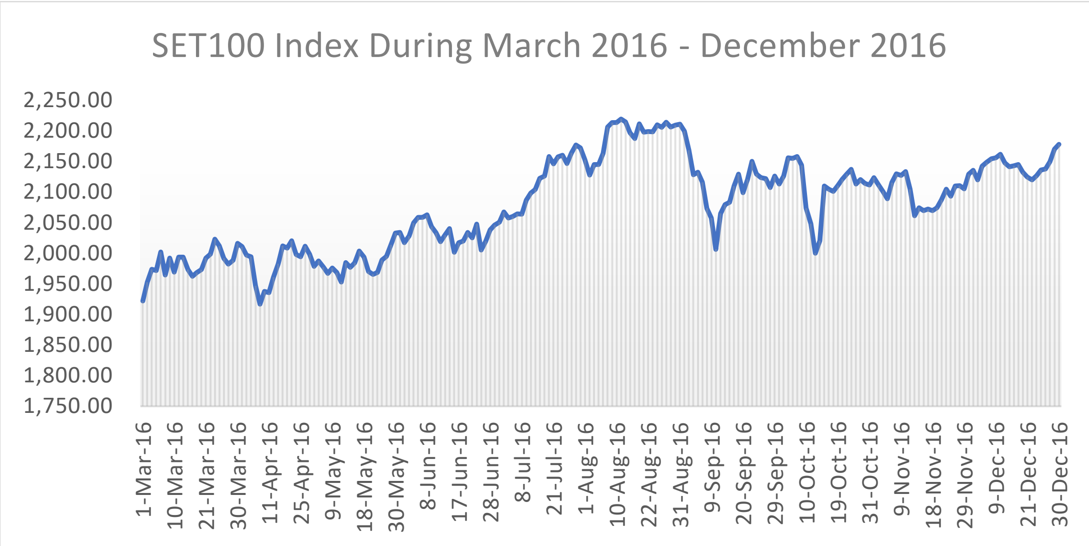

Figure 2.4 SET100 Index (March-December 2016)

I attained the data from the Stock Exchange of Thailand database. The data consists of the intraday order submission data and the intraday order transaction data of the stocks listed in the SET100 index during March 2016 to December 2016. The intraday order submission data is the detailed data of all the orders submitted to the stock exchange. It has the information about the type of investors (retail, institutional or foreign), order side (buy or sell), order type (market order, special market order, market to limit, ATO, ATC, IOC, FOK or Iceberg), price condition (market, limit, peg best bid, peg best offer, peg midpoint, market to level, special market), valid till, order number, trade price, trade size and cancel time. The intraday transaction data is the data of all the transaction executed in the stock exchange which composed of the data of the buyer and seller order time, trade price, trade size and the type of investors who engage in buying and selling. The SET100 stocks are one hundred stocks which have the largest average daily market capitalization for the past 3 months. All of the data are timestamped to the nearest millisecond. Datastream database provided the information on the market capitalization and the total number of outstanding stocks. They are used to compute the logarithmic of market capitalization and the share turnover.

The data is a panel data. The daily sample is composed of 20,400 observations for 204 trading days. One daily observation is equal to the set of dependent variables, independent variables and control variables for each stock on each day. I removed the data of non-trading day. Further, I eliminated the data on the days that the institutional or foreign investors have zero trading volume. The final number of observations is 20,299. Figure 2.5 and 2.6 illustrate the time plot of the algorithmic trading activities over time by date and month respectively. Figure 2.7 and 2.8 show the time plot of the algorithmic trading initiated by institutional investors over time by date and month respectively. Lastly, figure 2.9 and 2.10 display the time plot of the algorithmic trading activities initiated by foreign investors over time by date and month respectively.

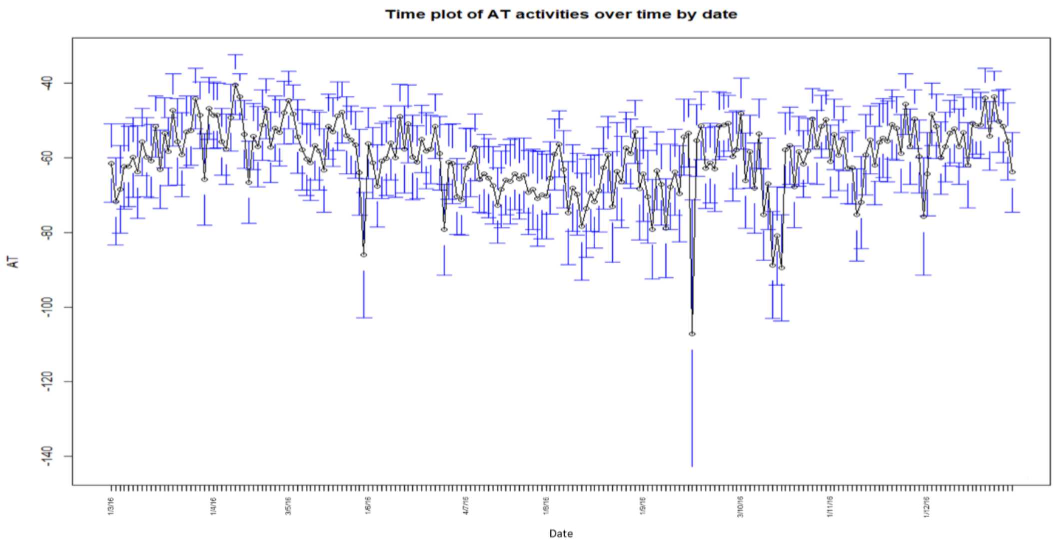

Figure 2.5 Time Plot of Algorithmic Trading Activities by Date

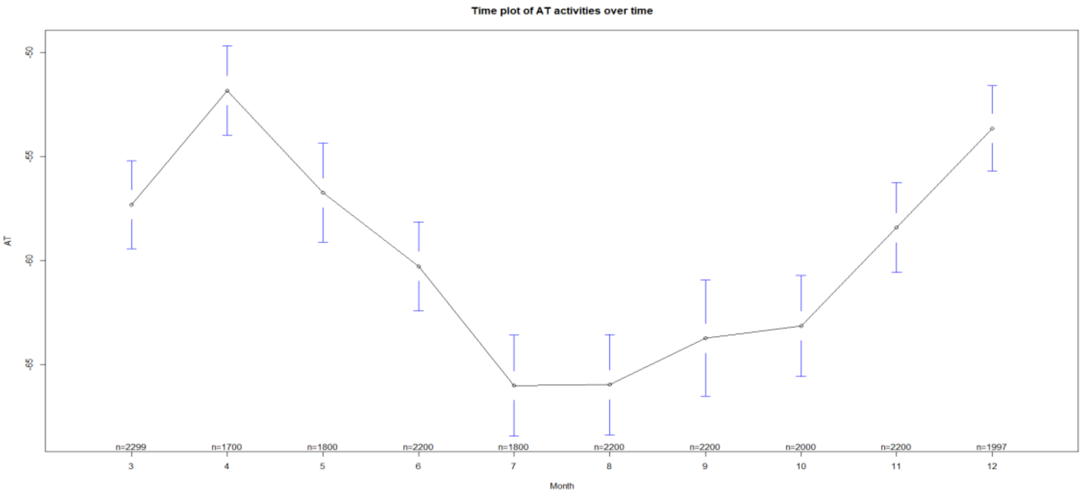

Figure 2.6 Time Plot of Algorithmic Trading Activities by Month

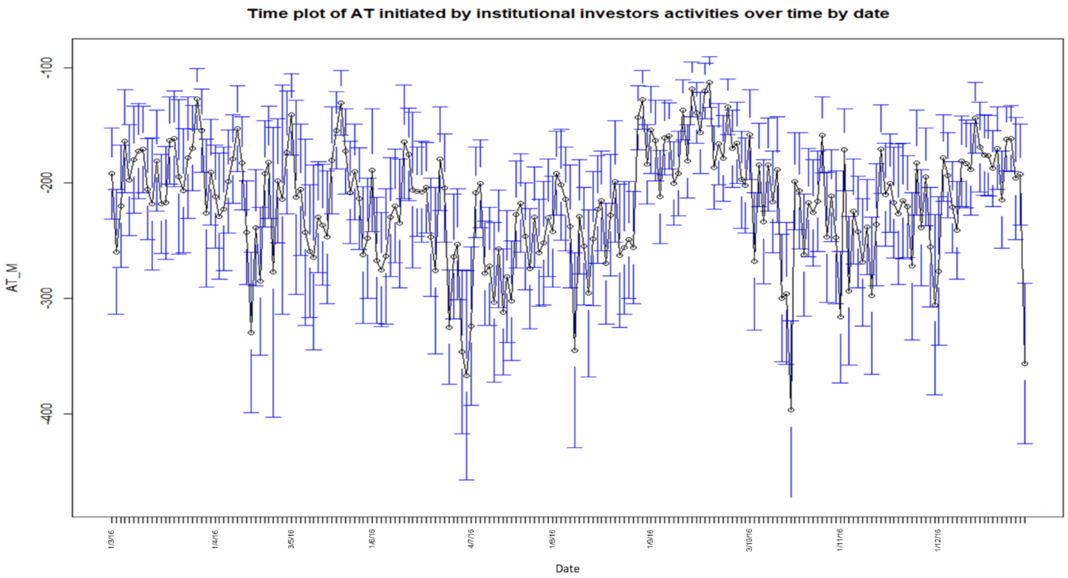

Figure 2.7 Time Plot of Algorithmic Trading Initiated by Institutional Investors Activities by Date

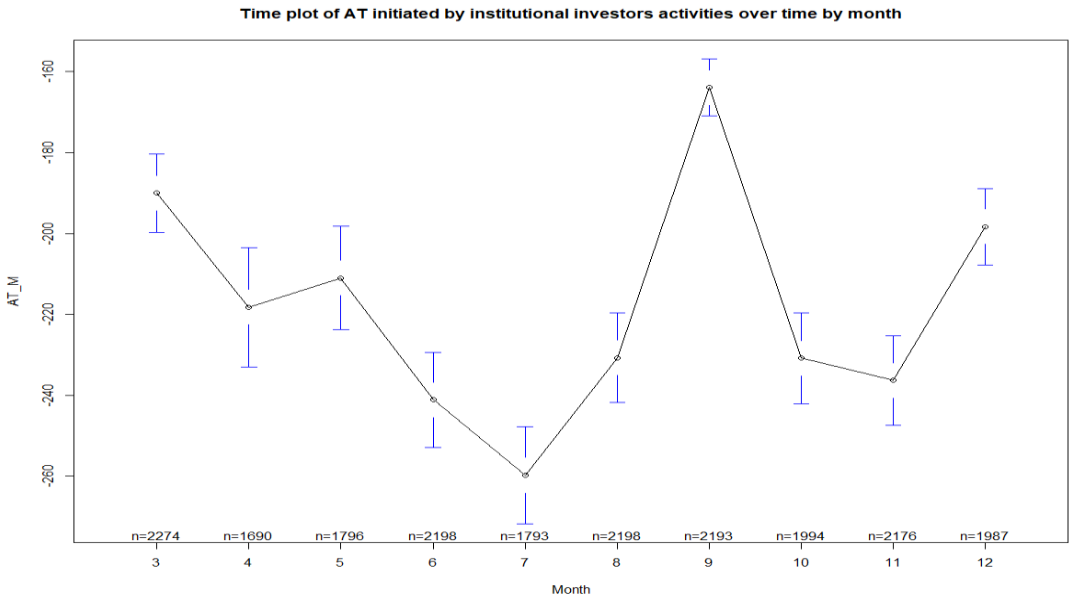

Figure 2.8 Time Plot of Algorithmic Trading Initiated by Institutional Investors Activities by Month

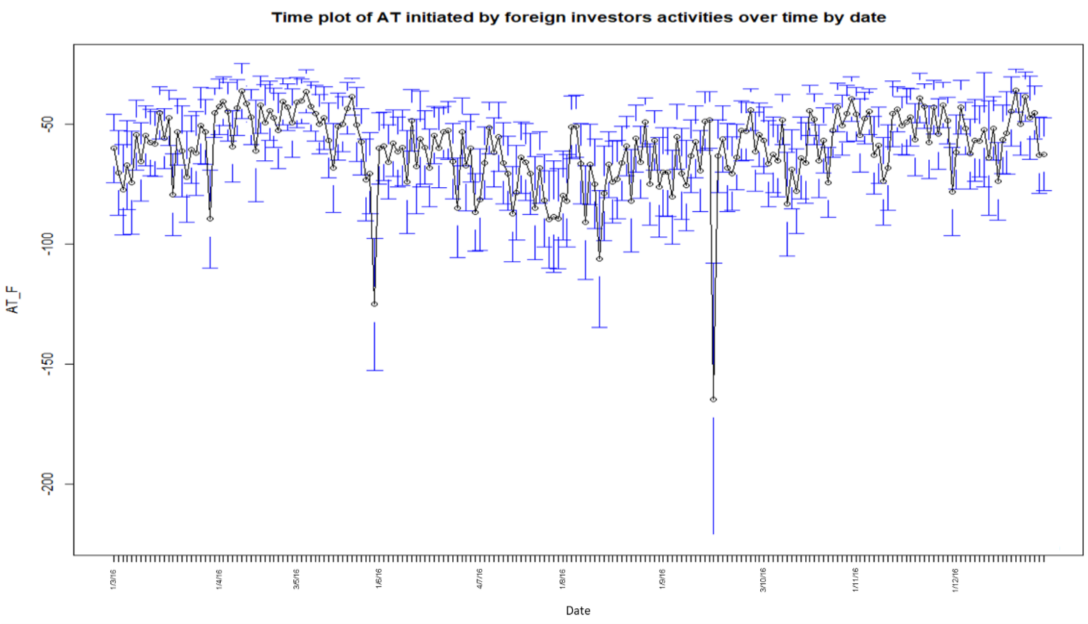

Figure 2.9 Time Plot of Algorithmic Trading Initiated by Foreign Investors Activities by Date

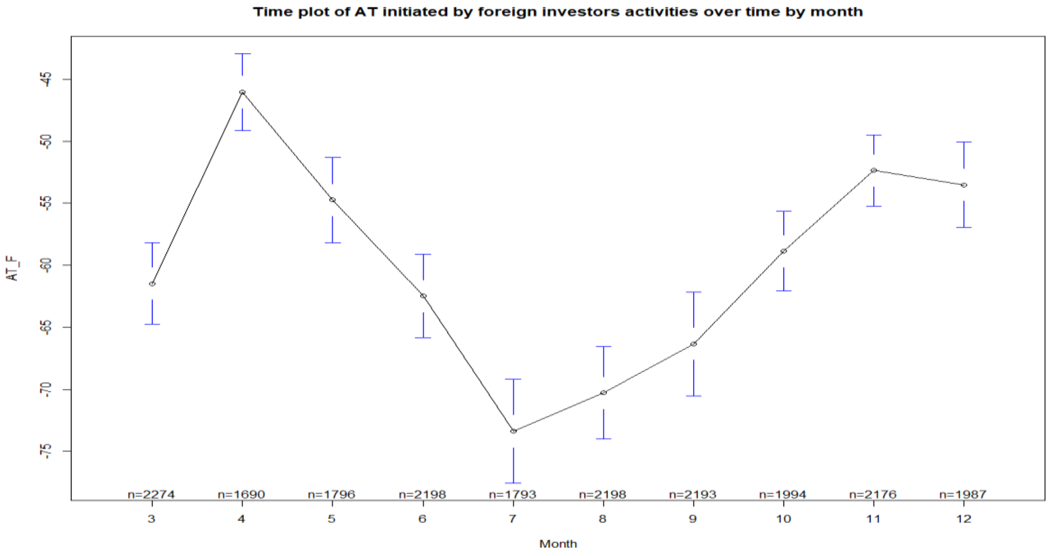

Figure 2.10 Time Plot of Algorithmic Trading Initiated by Foreign Investors Activities by Month

CHAPTER 3

THE IMPACT OF ALGORITHMIC TRADING ON VOLATILITY

3.1 Introduction

Algorithmic trading affects the behavior of traders in the stock market. It may increase the risk in the market. The dynamic asset pricing model describes three sources of risk, namely, cash flow risk, discount rate risk and volatility risk – each exerts a risk premium and therefore, an increase in volatility increases risk premium (Bansal, Kiku, Shaliastovich, & Yaron, 2014). Return volatility is the variation of the stock price process over time. Volatility captures the strength of the variations in price changes during certain period of time.

Return volatility is an essential issue to investors and firms as return volatility is associated with asset pricing, portfolio allocation, cost of capital and risk management. Higher volatility makes limit orders more expensive. Thus, it obstructs investor participation and deters risk sharing (Allen & Gale, 1994). Moreover, by holding volatile stocks, investors require higher rate of return, implying higher cost of capital to the firms (Lee, Ng, & Swaminathan, 2009). Schill (2004) demonstrated that market volatility affects the frequency of initial public offering (IPO) transaction. Furthermore, volatility in firm value changes the value of stock options and compensation to managers; hence, affecting the firms. In addition, it also affects the investors' portfolio values. Loungani, Rush, and Tave (1990b) showed that stock market dispersion significantly affects unemployment. In addition, Loungani, Rush, and Tave (1990a) found that the stock market dispersion is also related to business cycle. Therefore, in this chapter, I investigate the effect of algorithmic trading on risk, using the return volatility measure. This understanding is useful for policymakers, investors and firms. If algorithmic traders cause volatility to increase, this poses risks onto other investors and causes an increase in cost of capital for firms. Therefore, this may raise the need for regulation.

There are two competing reasons predicting the effect of algorithmic trading on volatility. On the one hand, algorithmic trading reduces volatility as high frequency market makers supply liquidity when there are large block orders, reducing price impact. On the other hand, algorithmic trading increases volatility because 1) algorithmic trading can trigger large price movement when there are large number of orders to be executed, 2) as algorithmic trading responds to new information faster, this may induce volatility, 3) momentum traders can trigger excessive price movement and 4) when institutional investors want to dissolve large position, HFT can trigger extreme volatilities by front-running orders submitted by slower institutional traders or engaging in quote stuffing strategy. The presence of algorithmic traders may affect volatility. Moreover, in an emerging market, it is found that volatility is more volatile (Bekaert & Harvey, 1997). Therefore, it is interesting to understand the differences between the impact of algorithmic trading on volatility in a developed market and the one in an emerging market. This study, thus, investigates the effect of algorithmic trading on volatility in the Stock Exchange of Thailand. Therefore, our research questions are:

RQ# 1: What is the effect of algorithmic trading on return volatility?

RQ# 2: Is there a causal relationship between algorithmic trading and return volatility?

RQ# 3: What is the effect of algorithmic trading initiated by each type of investors on return volatility?

RQ# 4: What is the effect of algorithmic trading on return volatility during the volatile period?

RQ# 5: Is there a causal relationship between algorithmic trading and return volatility during the volatile market?

RQ# 6: What is the effect of algorithmic trading initiated by each type of investors on return volatility during the volatile period?

3.2 Literature Review

3.2.1 Volatility

Returns are associated with risk, which is defined as the variance of the asset returns (Markowitz, 1952). There are two types of risk: systematic and unsystematic risk. Systematic risk is the risk associated with the economy and the market as a whole; whereas unsystematic risk or idiosyncratic volatility is due to individual effect. Merton (1987) showed that expected returns are subjected to unsystematic risk such as size of firms, the popularity of the firms, etc. Kumari, Mahakud, & Hiremath (2017) demonstrated that the variation in price returns or idiosyncratic volatility increases when the firm size is smaller, liquidity is higher, momentum is lower, the book-to-market ratio is higher and the cash flow-to-price is lower. Along the same line, Lee, Ng and Swaminathan (2009) found that firm-specific expected returns are associated with market beta, idiosyncratic volatility, leverage, book-to-market ratio, currency beta and firm size.

There are many determinants of return volatility. Traditionally, volatility is explained by the arrival of new information about payoff and discount rates. However, many researchers observe that large portions of variations in volatility cannot be explained by the efficient market model (LeRoy & Porter, 1981). Shiller (1981) found that variations in volatility can be explained by market psychology. Furthermore, volatility is affected by returns. Black (1986) and Duffie (2010) found that volatility increases after a decrease in returns. Another determinant of return is liquidity trading. Asset price can be altered due to a number of investors present in the market; therefore, volatility is affected by liquidity. Allen and Gale (1994) showed that when market participation is limited, a small liquidity shock results in a significant price volatility. Another explanation of the variation in asset returns is asymmetric information. Longin (1997) provided the theoretical model indicating that the asymmetric information causes nonlinearity in the expected volatility. Jones, Kaul, and Lipson (1994) provided the evidence that information contributes to the change in short-term return volatility. Similarly, Admati and Pfleiderer (1988) indicated that the rate of the availability of public information and the amount of nondiscretionary liquidity trading affect the level of volatility. Furthermore, they extended the Kyle (1985) model and showed that the number of informed investors in the market affects the price equilibrium.

Type of investors also affects volatility. Black (1986) suggested that a change in number of noise traders or in the characteristics of noise trading alters price volatility. Campbell and Kyle (1993) showed that noise traders increase securities volatility. Morck, Yeung, and Yu (2000) demonstrated that stock volatility is higher in an emerging economy due to larger noise or systematic risk that is unrelated to fundamentals. Foucault, Sraer, and Thesmar (2011) tested whether the trades initiated by retail investors affect idiosyncratic volatility. They showed that retail investors act like noise traders, raising volatility of the stock return. Vo (2016) reported a negative and significant relationship between institutional ownership and volatility on stock returns. In contrast, Sias (1996) described a positive contemporaneous relationship between institutional ownership and return volatility. A negative relationship between foreign ownership (LFO) and volatility is documented (Li, Nguyen, Pham, & Wei, 2011).

Volatility measurement is characterized into ex-post and ex-ante. Ex-post measurement is computed given the actual return observations. This can be calculated without models. Ex-ante or implied volatility is the forecast of future return volatility, based on current information set. There are two methods of volatility estimation and predictions: parametric and nonparametric approaches. Parametric procedure makes certain assumptions regarding the expected volatility, $\vartheta^2(t,h)$ such as the autoregressive conditional heteroskedastic (ARCH) model (Engle, 1982), whereas nonparametric volatility measurements quantify notional volatility, $v^2(t,h)$, directly from the ex-post returns.

3.2.2 Theoretical Model of the Effect of Algorithmic Trading on Volatility

Previous works model investors as fully rational individuals. Simon (1991) introduced the investors with bounded rationality. Furthermore, investors are heterogeneous with different preference (Weinbaum, 2009). The limit order book is modelled as a continuous double auction. Kirman (1993) and Alfarano, Lux, and Wagner (2005) provided the stochastic process of agent-based models of financial markets.

Several models are used to describe the effect of algorithmic trading on volatility. Xue and Gençay (2012) modelled different traders with heterogenous information. Cespa and Vives (2015) studied the effect of high frequency trading on market welfare. They modelled the trading equilibrium and found that the presence of high frequency traders causes the hedgers to consume more liquidity and induce higher volatility, causing liquidity fragility and eventually, the flash crashes. For the agency strategy, Gsell (2008) simulated the market with the participation of algorithmic traders. He showed that the low-latency traders decrease market volatility by slicing orders into smaller pieces and controlling the volume-weighted average price. Nonetheless, this simulation only included one type of algorithmic trading strategies. Therefore, the aggregate effects of various strategies may yield different results.

For the speculation strategies, Froot, Scharfstein, and Stein (1992) studied the effect of speculators' trading on asset prices. They found that if the speculators trade on short horizon, they base their decisions on the behaviors of the other traders, rather than the fundamental information. These behaviors of the speculators are similar to those of the high frequency traders. Hanson (2012) modelled the effect of high frequency traders using an agent-based simulation and founded that high frequency traders increase price volatility. Leal, Napoletano, Roventini, and Fagiolo (2016) provided an agent-based model of the interaction between low- and high-frequency trading assuming HFT uses directional strategies. Their simulation results showed that HFT increases volatility and helps to generate flash crashes.

3.2.3 Empirical Studies of The Effect of Algorithmic Trading on Volatility

Empirical studies yielded mixed results. Several studies proved that volatility is positively correlated with algorithmic trading, deteriorating market quality. For the U.S. stocks, Zhang (2010) reported a positive relationship between high frequency trading and volatility. In addition, their effects were more substantial for the stocks in Russell 3000 Index, the stocks with high institutional investors holdings, and when the markets were more volatile. For the 35 major stocks listed in Borsa Italiana market during 2011-2013, Caivano (2015) investigated the impact of high frequency trading on volatility by using a change in market microstructure as an instrumental variable and showed that high frequency trading enhanced volatility. Boehmer, Fong, and Wu (2015) carried out the study of the effect of algorithmic trading on volatility in 42 international markets and drew the conclusion that algorithmic trading increased the short-term volatility. As a better representation of the impact of algorithmic trading onto other types of traders, Kelejian and Mukerji (2016) used a daily volatility to examine the relationship between high frequency trading and volatility. They revealed that high frequency trading intensifies volatility.

On the other hand, other studies found that the relationship between algorithmic trading and volatility is negative, inferring that an increase in algorithmic trading reduces volatility. Westerholm (2016) investigated the relation between high frequency trading and price volatility on the stocks listed in the NASDAQ OMX Helsinki Stock Exchange between 2007 and 2009 and found that it is negative. The effect persists even during the uncertain periods. Hagströmer and Nordén (2013) identified market-making and opportunistic high frequency traders in the NASDAQ-OMX Stockholm stocks and found that both types of high frequency traders decrease intraday volatility while an increase in tick size does not affect intraday volatility. Brogaard (2011) utilized the NASDAQ OMX dataset which identified high frequency traders from non-high frequency traders. He applied vector autoregression (VAR) to demonstrate that high frequency trading is associated with negative volatility. However, when studied the impact of algorithmic trading on volatility, they found no evidence that high frequency trading increases volatility. Similar result prevailed in the foreign exchange market. Volatility is negatively associated with algorithmic trading, but no causal relationship is found (Chaboud et al., 2014). Other studies found no evidence that algorithmic trading is associated with volatility (Hendershott & Riordan, 2009).

One of the important events for the empirical study of the relationship between algorithmic trading and volatility is the flash crash. The flash crash of May 6, 2010 caused major U.S. equity indices such as Dow Jones Industrial Average, S&P etc., to drop substantially and regained most of their pre-drop levels within 26 minutes. This event generated unusually high intraday volatility and extremely low intraday liquidity and resulted in trillion of dollars loss. Many claimed that high frequency trading was a cause of such volatility spike. Investigating the Flash Crash 2010 event, Kirilenko, Kyle, Samadi, and Tuzun (2017) demonstrated that the trading pattern and the inventory level of market-making high frequency traders did not change in response to large and temporary changes in prices on May 6, 2010, which was consistent with the theory of limited risk-bearing capacity. In conclusion, they argued that high frequency trading did not cause the flash crash but helped to amplify market volatility. Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2018) examined the role of liquidity-providing HFT around the event of extreme price movements and found that during extreme volatility, liquidity providers did not withdraw their positions and still provided liquidity to other types of investors and there was no evidence that high frequency traders caused extreme price movements.

3.3 Sample and Methodology

3.3.1 Algorithmic Trading Measurement *(AT)*

The major challenge of this type of empirical research is the difficulty to identify and measure algorithmic trading activities. In general, to capture algorithmic trading, we need to be able to access the limit order book information and identify whether the orders are submitted by algorithmic traders or not. Several researchers have access to this type of information. They are Hagströmer and Nordén (2013), Menkveld (2013) and Caivano (2015). However, this information is often difficult to obtain. Therefore, researchers use indirect method to capture algorithmic trading activities. Carrion (2013) detected algorithmic trading activities based on their behaviors. Hasbrouck and Saar (2013) measured "strategic runs" of the linked messages used by proprietary high frequency traders to place their orders which involves a large quantity of consecutive submissions and cancellations. Finally, Hendershott, Jones, and Menkveld (2011) used a normalized message traffic as a proxy for algorithmic trading. Message traffic includes all submissions (buy, sell and revision), cancellation and trade report. The rationale is that while algorithmic traders increase the number of message traffic, the ratio of the number of the orders that get executed to the total number of orders decreases.

Due to the data unavailability, I cannot directly measure algorithmic trading activity. I followed the method of Hendershott et al. (2011) who used a normalized message traffic as a proxy for algorithmic trading. The message traffic is the sum of all messages in both order data, which included all buys, sells, revisions and cancellations, and deal data which contained all the trade reports. Hence, I measured the algorithmic trading using the following formula:

$$AT_{it} = \frac{-V_{it}}{MT_{it}} \tag{3.1}$$

where AT_{it} is the proxy for algorithmic trading for stock *i* at day *t*, V_{it} is the trading volume for stock *i* at day *t* and MT_{it} is the traffic message for stock *i* at day *t*.

3.3.2 Volatility Measurement

3.3.2.1 Realized Volatility (RV)

Most studies use the standard deviation of the return as the measure of volatility. I used the historical or realized volatility to measure the variability of the prices of the stocks. I assumed the return process to be covariance stationary with

$$\sigma_{it} = \sqrt{var(R_{it})} = \sqrt{E[(R_{it} - E[R_{it}])^2]}, \tag{3.2}$$

where R_{it} is the stock return. The sample estimate of the volatility of the return process can be defined as:

$$RV_{it} = \sqrt{\frac{\sum_{t=1}^{d}(R_{it} - \bar{R})^2}{d-1}}, \tag{3.3}$$

where RV_{it} is the realized volatility, $\bar{R}$ is the mean stock return and d is the number of periods during the measured time. As the return observation is subjected to microstructure effects, such as noise, bid-ask bounce, discrete price grids, etc., interval return is used instead of instantaneous price. The frequency of sampling is difficult to identify. For robustness, I performed one-minute and five-minute intraday realized volatilities. Therefore, the one-minute realized volatility can be defined as:

$$RV_{it}^{1min} = \sqrt{\frac{\sum_{t=1}^{d}(R_{it} - \bar{R})^2}{d-1}}, \tag{3.4}$$

where R_{it} is the stock return sampling the prices at every one minute. The five-minute realized volatility can be defined as:

$$RV_{it}^{5min} = \sqrt{\frac{\sum_{t=1}^{d}(R_{it} - \bar{R})^2}{d-1}}, \tag{3.5}$$

where R_{it} is the stock return sampling the prices at every five minute.

3.3.2.2 Range-based Volatility (RBV)

Another measure of volatility is the range-based volatility (RBV_{it}). It is defined as the natural logarithm of the ratio of the daily high (P_{it}^{H}) trading price to the daily low (P_{it}^{L}) trading price.

$$RBV_{it} = \ln\left(\frac{P_{it}^{H}}{P_{it}^{L}}\right). \tag{3.6}$$

3.3.3 Control Variables

Confounding is one of the major issues with establishing the causal relationship between algorithmic trading and volatility and therefore, control variables are included to eliminate the confounding effects. Control variables are the variables which affect volatility. As volatility is associated with stock returns, volatility is related to firm size and value (Cheung & Ng, 1992; Fama & French, 1992). Cheung and Ng (1992) demonstrated that small firms tend to associate with higher level of volatility. Bushee and Noe (2000) showed that volatility is positively correlated with firm value. Subsequently, firm size is represented by the market capitalization and firm value is represented by the market-to-book ratio.

Numerous studies found that higher trading volume is associated with higher return variations (Jain & Joh, 1986; Wood, McInish, & Ord, 1985). Theoretical models are used to explain the relationship between return volatility and trading volume. Admati and Pfleiderer (1988) provided the intraday pattern model with the interaction between liquidity traders and informed traders and disclosed that return variability is higher during the period of high trading volume. Wang and Yau (2000) showed that volatility is positively associated with trading volume, consistent with the empirical result obtained by Foster and Viswanathan (1993).

Moreover, bid-ask spread and volatility are related according to Zhang, Russell, and Tsay (2001). Wang and Yau (2000) found a positive relationship between bid-ask spread and volatility. Weber and Rosenow (2006) investigated the extreme price movement and found that liquidity contributes to the occurrence of extreme price movement. Furthermore, I used the inverse of price as a proxy for transaction cost and tick size, which affects the volatility (Hau, 2006, p. 2006). Upon a change in tick size in Taiwan Stock Exchange, Ke, Jiang, and Huang (2004) documented a positive relationship between volatility and tick size. As a result, I included the logarithmic of market capitalization, the book-to-market ratio, the share turnover, the inverse of price and the bid-ask spread as the control variables.

3.3.4 Model Specification

3.3.4.1 Linear Regression Model

In this section, I found the appropriate model to establish the relationship between algorithmic trading and volatility. A regression analysis is the simple but powerful method of statistical analysis on relating multiple variables by calculating the best fit line. For robustness, I used multiple volatility measures and to avoid confounding effects, I included the control variables. As a result, I conducted a multivariate regression analysis using ordinary least square. The model specification is as following:

$$RV_{it}^{1min} = \alpha + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.7)$$

$$RV_{it}^{5min} = \alpha + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.8)$$

$$RBV_{it} = \alpha + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.9)$$

Furthermore, the independent variables may be correlated with each other. This problem is called multicollinearity. This problem causes the model to be unstable. To assess the possible presence of multicollinearity, the variance inflation factor (VIF) is used to measure the inverse of 1 - R-square for the regression with the tested predictor as the dependent variable on other independent variables. This evaluates the inflation of the variance of a coefficient due to the dependence with other independent variables. Therefore, I computed the variance inflation factor to ensure that all regressors are not subjected to multicollinearity. Multiple regressions were performed with the null hypothesis being there is no relation between algorithmic trading and volatility. The description of dependent and independent variables is listed in Table 3.1.

Table 3.1 Description of the Variables

Variables	Description
Dependent	
RV^{1min}	One-minute realized volatility
RV^{5min}	Five-minute realized volatility
RBV	Range-based volatility
Independent	
AT	Algorithmic trading. The negative ratio of the volume traded to the traffic messages
P/B RATIO	Price-to-book ratio indicates the ratio of the market value of the firm to the book value
TURNOVER	Share turnover is the total number of shares traded by the average number of shares outstanding over a period
PRICE	The daily average price traded
SPREAD	The end of the day bid-ask spread
MARKET CAP	Market capitalization is the total market value of a company's outstanding shares

Therefore, the null hypothesis is defined as:

H_0: $\beta_1 = 0$

H_1: β_1 is not equal to 0

As traders make decisions from the behaviors of other traders and algorithmic traders tends to trade in small-sized orders, we hypothesize that algorithmic traders are noise traders, and thereby, increase volatility.

To analyze the multiple regression models, it is initially assumed that there is no heterogeneity in the variables. Therefore, I analyzed the model using the pooled OLS regression. The pooled OLS model has the following assumptions:

(1) $E(\varepsilon_{it}) = 0$,

(2) There is no perfect collinearity,

(3) There is no endogeneity,

(4) The variables are homoscedasticity,

(5) The cross-sectional and time-series observations are not correlated,

(6) The disturbance term has a normal distribution.

Peterson (2009) claimed that there might be an unobserved heterogeneity when using the pooled OLS regression. The residuals from the pooled OLS might be correlated by: 1) the individual effect which happens when the residuals are correlated across time for a given stock and 2) the time effect which occurs when the residuals are correlated across individuals for a given time. In the other word, there are variations across stock or time units of observations. Therefore, their standard errors are biased. As a result, the individuality is summed up in the disturbance term (ε_{it}), causing the estimated coefficients (β_i) to be biased and inconsistent. Alternatively, the disturbance term can be written as $\varepsilon_{it} = \alpha_i + u_{it}$, where α_i is the heterogeneity effect and u_{it} is the error term.

To address the heterogeneity problem, I eliminated the fixed effects (α_i). There are two methods in doing so: the fixed-effect estimator (FE) and the random effects model (REM). The fixed-effect estimator removes the fixed effects by expressing the variables for each individual as the deviation from their mean. On the other hand, the random effects model assumes that the error terms are random variables. Therefore, I expressed equation 3.7 to 3.9 as the fixed effects models:

$$RV_{it}^{1min} = \beta_1 \overline{AT_{it}} + \beta_2 P/B\ RATIO_{it} + \beta_3 \overline{TURNOVER_{it}} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 \overline{SPREAD_{it}} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.10)$$

$$RV_{it}^{5min} = \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.11)$$

$$RBV_{it} = \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 \overline{SPREAD_{it}} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.12)$$

where RV_{it}^{1min}, RV_{it}^{5min} and RBV_{it} are the mean-corrected values for volatility measures i.e. one-minute realized volatility, five-minute realized volatility and range-based volatility for stock i on day t. AT_{it} is the mean-corrected value of the algorithmic trading proxy for stock i on day t. $P/B\ RATIO_{it}$, $TURNOVER_{it}$, $\left(\frac{1}{PRICE}\right)_{it}$, $SPREAD_{it}$, and $LN(MARKET\ CAP)_{it}$ are the mean-corrected values for the price-to-book ratio, the share turnover, the inverse of average price, the spread and the natural logarithm of market capitalization for stock i on day t. As a result, I conducted the individual, time and two-ways within-group fixed-effects models.

The random-effects models can be expressed as:

$$RV_{it}^{1min} = \alpha + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + w_{it} \quad (3.13)$$

$$RV_{it}^{5min} = \alpha + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + w_{it} \quad (3.14)$$

$$RBV_{it} = \alpha + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + w_{it} \quad (3.15)$$

where

$$w_{it} = \varepsilon_i + u_{it} \quad (3.16)$$

w_{it} is the composite error terms, composing of two components: the individual-specific error component (ε_i) and the idiosyncratic term (u_{it}) which combine both individual and time error components.

To establish the appropriate models, I performed two tests: restricted F-test and Hausman test. The restricted F test is used to determine whether there exist heterogeneity issues or not. Formally, I can express the model for testing the null hypothesis of the restricted F-test as:

$$RV_{it}^{1min} = \alpha_1 + \alpha_2 D_{2i} + \cdots + \alpha_n D_{ni} + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.17)$$

$$RV_{it}^{5min} = \alpha_1 + \alpha_2 D_{2i} + \cdots + \alpha_n D_{ni} + \beta_1 AT_{it} + \beta_2 \frac{P}{B} RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.18)$$

$$RBV_{it} = \alpha_1 + \alpha_2 D_{2i} + \cdots + \alpha_n D_{ni} + \beta_1 AT_{it} + \beta_2 P/B\ RATIO_{it} + \beta_3 TURNOVER_{it} + \beta_4 \left(\frac{1}{PRICE}\right)_{it} + \beta_5 SPREAD_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.19)$$

where $D_{2i} = 1$ for stock 2 and zero otherwise and D_{ni} = 1 for stock n and zero otherwise. The null hypothesis for these models is that the differential intercepts are equal to zero.

H_0: α_i = 0 for $\forall\ i = 2, \ldots, n$

H_a: At least one α_i is not equal to 0.

In addition, to choose between the fixed-effects and the random effects models, the Hausman test is the selection tool. The Hausman test asserts that w_{it} is correlated with independent variables. The null hypothesis tests the significance of:

$$W = (\beta_{RE} - \beta_{FE})'\hat{\Sigma}^{-1}(\beta_{RE} - \beta_{FE}) \sim \chi^2(k) \tag{3.20}$$

where β_{RE} is the random effects estimator, β_{FE} is the fixed effects estimator and $\hat{\Sigma}^{-1}$ is their covariances.

3.3.4.2 Two-stage Least Squares Estimation

Algorithmic trading proxy and volatility may be endogenous variables. While Hendershott and Riordan (2009) found that algorithmic trading is not related to past volatility, Brook, Sharp, Ushaw, Blewitt, and Morgan (2013) showed that the algorithm developers design the trading algorithms to react to the market volatility. In addition, Brogaard (2011) showed that a change in idiosyncratic volatility causes the high frequency traders to change their aggressiveness.

Therefore, to solve for possible endogeneity and to establish the causal relationship, I applied the two-stage least squares (2SLS) estimation technique to produce regression estimators for the relationship between algorithmic trading and volatility. This estimation method requires a proper instrumental variable (IV_{it}).

Since 1991, The Stock Exchange of Thailand (SET) has utilized the computerized trading system. In 2012, SET upgraded the “SET CONNECT” system to improve the transaction speed and facilitate foreign investors to invest in the market. However, algorithmic traders participated in the Stock Exchange of Thailand during that period is still premature. Therefore, using these two incidents as instrumental variables is not appropriate.

However, during October 2016, the market data displayed the participation of algorithmic traders and the market encountered a brief flash crash. I used this event as an instrumental variable for the participation of algorithmic trading in the Stock Exchange of Thailand. Thereby, I instrumented the algorithmic trading activities with the instrumental variable. This assumed that algorithmic trading activities was higher after October 2016 than the one before October 2016. The dummy variable called IV_t is equal to 1 after October 2016 and 0 otherwise. Two assumptions are made for the instrumental variables: 1) the dummy variable IV_{it} is not correlated with the error term, and 2) the dummy variable IV_{it} is correlated with the independent variables so that the regression coefficients remain consistent.

Therefore, the first stage regression is:

$$\widehat{AT}_{it} = \alpha + \beta_1 IV_{it} + \beta_2 LN(MARKET\ CAP)_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 SPREAD_{it} + \mu_{it}. \tag{3.21}$$

In the second stage regression, the relationship between algorithmic trading and volatility models can be expressed as following:

$$RV_{it}^{1min} = \alpha + \beta_1 \widehat{AT}_{it} + \beta_2 LN(MARKET\ CAP)_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 SPREAD_{it} + \mu_{it}. \tag{3.22}$$

$$RV_{it}^{5min} = \alpha + \beta_1 \widehat{AT}_{it} + \beta_2 LN(MARKET\ CAP)_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 SPREAD_{it} + \mu_{it}. \tag{3.23}$$

$$RBV_{it} = \alpha + \beta_1 \widehat{AT}_{it} + \beta_2 LN(MARKET\ CAP)_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 SPREAD_{it} + \mu_{it}. \tag{3.24}$$

3.3.4.3 Granger Causality Test

Alternatively, to establish the causal relationship and alleviate the endogeneity problem, I conducted the Granger causality test between algorithmic trading and volatility measures. For a panel data, there are many estimation techniques such as a GMM estimator, a SUR estimator and a multivariate least square estimator. I employed the multivariate least square estimator (Dumitrescu & Hurlin, 2012, pp. 1450-1460), which extends the work of Granger (1969). The interaction between algorithmic trading and volatility measures can be modelled using a panel data vector autoregressive (VAR).

$$RV_{it}^{1min} = \beta_{0i} + \sum_{j=1}^{n} \alpha_{i,j} AT_{i,t-j} + \sum_{k=1}^{n} \beta_{i,k} RV_{i,t-k}^{1min} + u_{1i,t} \tag{3.25}$$

$$AT_{i,t} = \lambda_{0i} + \sum_{j=1}^{n} \lambda_{i,j} AT_{i,t-j} + \sum_{k=1}^{n} \delta_{i,k} RV_{i,t-k}^{1min} + u_{2i,t}. \tag{3.26}$$

$$RV_{it}^{5min} = \beta_{0i} + \sum_{j=1}^{n} \alpha_{i,j} AT_{i,t-j} + \sum_{k=1}^{n} \beta_{i,k} RV_{i,t-k}^{5min} + u_{1i,t} \quad (3.27)$$

$$AT_{i,t} = \lambda_{0i} + \sum_{j=1}^{n} \lambda_{i,j} AT_{i,t-j} + \sum_{k=1}^{n} \delta_{i,k} RV_{i,t-k}^{5min} + u_{2i,t}. \quad (3.28)$$

$$RBV_{i,t} = \beta_{0i} + \sum_{j=1}^{n} \alpha_{i,j} AT_{i,t-j} + \sum_{k=1}^{n} \beta_{i,k} RBV_{i,t-k} + u_{1i,t} \quad (3.29)$$

$$AT_{i,t} = \lambda_{0i} + \sum_{j=1}^{n} \lambda_{i,j} AT_{i,t-j} + \sum_{k=1}^{n} \delta_{i,k} RBV_{i,t-k} + u_{2i,t}. \quad (3.30)$$

The Dumitrescu-Hurlin test makes the following assumptions: (i) the observations of the variables are time-stationary, (ii) the panel data is balanced, and (iii) the lag orders are the same for all stocks. Therefore, I conducted the unit root tests for both variables using Choi (2001)'s test statistics. The null hypothesis for the Dumitrescu-Hurlin test is that the coefficient for the lagged algorithmic trading terms in the equation 3.25, 3.27 and 3.29 do not fit in the regression, implying that algorithmic trading does not cause volatility measures to change. The alternative hypothesis is that at least one coefficient for the lagged algorithmic trading for some stocks is not equal to zero.

H_0: $\alpha_{i,j} = 0$ for all stock i and all lag j

H_1: $\alpha_{i,1} = \ldots = \alpha_{i,n} = 0$ for all i = 1 , ..., N_1

$\alpha_{i,1} \neq 0$ *or ... or* $\alpha_{i,n} \neq 0$ *for all i =* $N_1 + 1$ *, ..., N*

For Equation 3.26, 3.28 and 3.30, to determine whether volatility causes the change in algorithmic trading, the null hypothesis is defined as below.

H_0: $\delta_{i,j} = 0$ for all stock i and all lag j

H_1: $\delta_{i,1} = \ldots = \delta_{i,n} = 0$ for all i = 1, ..., N_1

$\delta_{i,1} \neq 0$ *or ... or* $\delta_{i,n} \neq 0$ *for all i =* $N_1 + 1$ *, ..., N*

The Dumitrescu-Hurlin tests analyze equation 3.25 to 3.30 using VAR for each stock and computed the F-statistics for each stock using the Wald test. The test statistics is calculated as the average of the Wald statistics for each stock. It is hypothesized that volatility should create the opportunity for algorithmic traders to make profit. Therefore, volatility should Granger cause AT to increase. However, the causality of algorithmic trading on volatility is unclear, depending on the magnitude and direction of their activities.

3.3.4.4 Volatile Market

To explore the effect of algorithmic trading on volatility during the volatile market, I conducted the hypothesis testing during the volatile market. The volatile market is characterized by the period when the stock market indices are the most fluctuated. Table 3.2 exhibits the monthly SET index volatility. For our sample, October 2016 is the most volatile period.

Table 3.2 Monthly SET Index Volatility

Month	**SET Index Volatility**
March 2016	0.8039%
April 2016	0.8723%
May 2016	0.6041%
June 2016	0.7320%
July 2016	0.4541%
August 2016	0.5886%
September 2016	1.1805%
October 2016	1.4559%
November 2016	0.6617%
December 2016	0.4423%

According to Biais et al. (2013), an increase in volatility leads algorithmic traders to trade more. Therefore, the magnitude of the effect of algorithmic trading should amplify during the volatile market. Hence, the coefficient of algorithmic trading during the volatile market should be positive and higher than the one during the entire period. I used the panel data analysis to establish the relationship between algorithmic trading and volatility measures. Furthermore, I used the Granger causality test to determine whether there is a bilateral causal relationship between algorithmic trading and volatility measures during the volatile market. It is hypothesized that the coefficient of algorithmic trading should be significant during the volatile period as high volatility should induce algorithmic traders to participate and thus, AT should cause the volatility to change.

3.3.5 Model Extension

As algorithmic traders need to gain the access to Direct market access service (DMA) provided by the Stock Exchange of Thailand, it is likely that the main group of algorithmic traders in the Stock Exchange of Thailand are institutional and foreign investors. Both types of investors are informed investors with different level of information advantages (Dvořák, 2005). Therefore, it is interesting to determine whether the use of technology changes the level of information advantages of these two types of investors and how it affects return volatility. By investigating these variables, I can better quantify the algorithmic trading measurement. As a result, one can comprehend the effect of algorithmic trading initiated by institutional investors vs foreign investors on market quality. Therefore, I developed the new proxies to capture the activities of algorithmic trading initiated by foreign and institutional investors. Algorithmic trading initiated by institutional investors is calculated as:

$$AT_{it}^{I} = \frac{-V_{it}^{I}}{MT_{it}^{I}} \tag{3.31}$$

And, algorithmic trading initiated by foreign investors is measured as:

$$AT_{it}^{F} = \frac{-V_{it}^{F}}{MT_{it}^{F}} \tag{3.32}$$

where AT_{it}^{I} and AT_{it}^{F} are the proxies for algorithmic trading initiated by institutional and foreign investors respectively. V_{it}^{I} and V_{it}^{F} are trading volumes in Thai Baht initiated by institutional and foreign investors respectively. MT_{it}^{I} and MT_{it}^{F} are the message traffic for stock i on day t initiated by institutional and foreign investors respectively.

To establish the relationship between algorithmic trading initiated by each types of investors on volatility, I employed the panel data regression analysis. As the effects of algorithmic trading initiated by institutional and foreign investors occur simultaneously, I included both terms in the model. Furthermore, to study the interaction between algorithmic trading initiated by institutional investors and one initiated by foreign investors, I incorporated the interaction term between these two variables into the models. Therefore, I can express the regression models as follows:

$$RV_{it}^{1min} = \alpha + \beta_1 AT_{it}^I + \beta_2 AT_{it}^F + \beta_3 AT_{it}^I AT_{it}^F + \beta_4 P/B\ RATIO_{it} + \beta_5 TURNOVER_{it} + \beta_6 \left(\frac{1}{PRICE}\right)_{it} + \beta_7 SPREAD_{it} + \beta_8 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.33)$$

$$RV_{it}^{5min} = \alpha + \beta_1 AT_{it}^I + \beta_2 AT_{it}^F + \beta_3 AT_{it}^I AT_{it}^F + \beta_4 P/B\ RATIO_{it} + \beta_5 TURNOVER_{it} + \beta_6 \left(\frac{1}{PRICE}\right)_{it} + \beta_7 SPREAD_{it} + \beta_8 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.34)$$

$$RBV_{it} = \alpha + \beta_1 AT_{it}^I + \beta_2 AT_{it}^F + \beta_3 AT_{it}^I AT_{it}^F + \beta_4 P/B\ RATIO_{it} + \beta_5 TURNOVER_{it} + \beta_6 \left(\frac{1}{PRICE}\right)_{it} + \beta_7 SPREAD_{it} + \beta_8 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (3.35)$$

Hence, the null hypothesis is formed to test whether there exists no relationship between algorithmic trading and volatility.

H_0: $\beta_1 = \beta_2 = \beta_3 = 0$

H_1: At least one β is not equal to 0.

To understand the effect of algorithmic trading initiated by institutional and foreign investors on volatility during the volatile market, I ran the regression using the data during the volatile period which is in October. The model utilizes the Equation 3.33 to 3.35 using the dataset during October 2016 to test the above null hypothesis.

3.3.6 Descriptive Statistics

In order to conduct the panel data Granger causality test, the unbalanced data is eliminated. The descriptive statistics is shown in Table 3.3. The average of one-minute and five-minute realized volatilities are 0.2920 and 0.4048 percent respectively. Range-based volatility averages at 0.0263. The average of the algorithmic trading proxy is -42.1811 and the standard deviation of the algorithmic trading proxy is 37.0363. The average of the algorithmic trading initiated by institutional investors proxy is -98.5739 and the standard deviation of the algorithmic trading proxy is 93.7883. The average of the algorithmic trading initiated by foreign investors proxy is -40.3647 and the standard deviation of the algorithmic trading proxy is 48.7118. Therefore, the mean of the algorithmic trading initiated by institutional investors is smaller than the one of the algorithmic trading initiated by foreign investors. So, foreign investors initiate more traffic messages. Therefore, there are more algorithmic trading activities initiated by foreign investors. On average, the market capitalization is 117 billion baht, the price-per-book ratio is 3.4700 and the share turnover is 0.0043. The average of the inverse of the average price and the effective half spread are 0.1034 and 0.2731 percent respectively. Figure 3.1 to 3.3 provide the time series plot of one-minute realized volatility, five-minute realized volatility and range-based volatility vs. algorithmic trading activity accordingly.

Table 3.3 Summary Statistics

Variables	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Dependent Variables					
One-minute realized volatility (%)	0.2920	0.2742	0.1096	0.0000	2.3374
Five-minute realized volatility (%)	0.4048	0.3861	0.1450	0.0000	3.1380
Range-based volatility	0.0263	0.0226	0.0162	0.0025	0.0284
Independent variables					
Algorithmic trading proxy (all)	-42.1811	-30.9240	37.0363	-1006.93	-1.9105
Algorithmic trading proxy (institutional investors)	-98.5739	-70.0395	93.7883	-1289.32	-0.0047
Algorithmic trading proxy (foreign investors)	-40.3647	-23.5131	48.7118	-1555.68	-0.0071
Stock Characteristics					
Market capitalization (Billion Baht)	117.02	48.43	171.34	7.43	1,047.51

Table 3.3 (Continued)

Variables	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Price-to-book ratio	3.4700	2.2800	3.5588	0.5600	27.7200
Share turnover	0.0043	0.0026	0.0058	5.82×10^{-5}	0.1246
The inverse of share price (1/Baht)	0.1034	0.0454	0.1364	0.0018	0.6824
Effective Half Spread (%)	0.2731	0.2490	0.1284	0.0000	1.1958

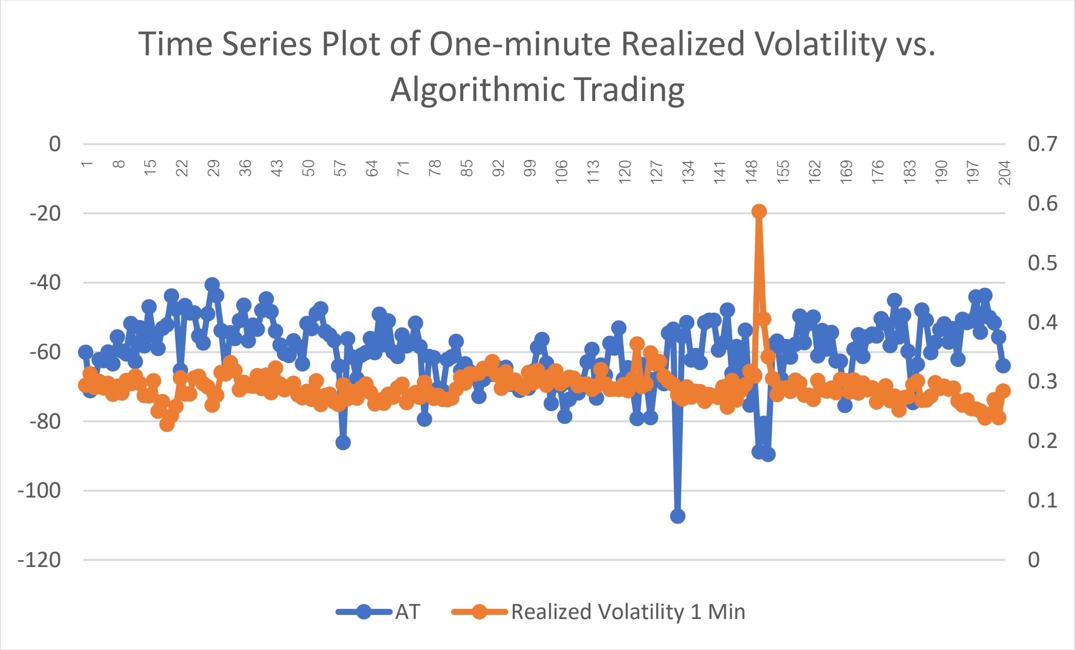

Figure 3.1 Time Series Plot of One-minute Realized Volatility vs. Algorithmic Trading

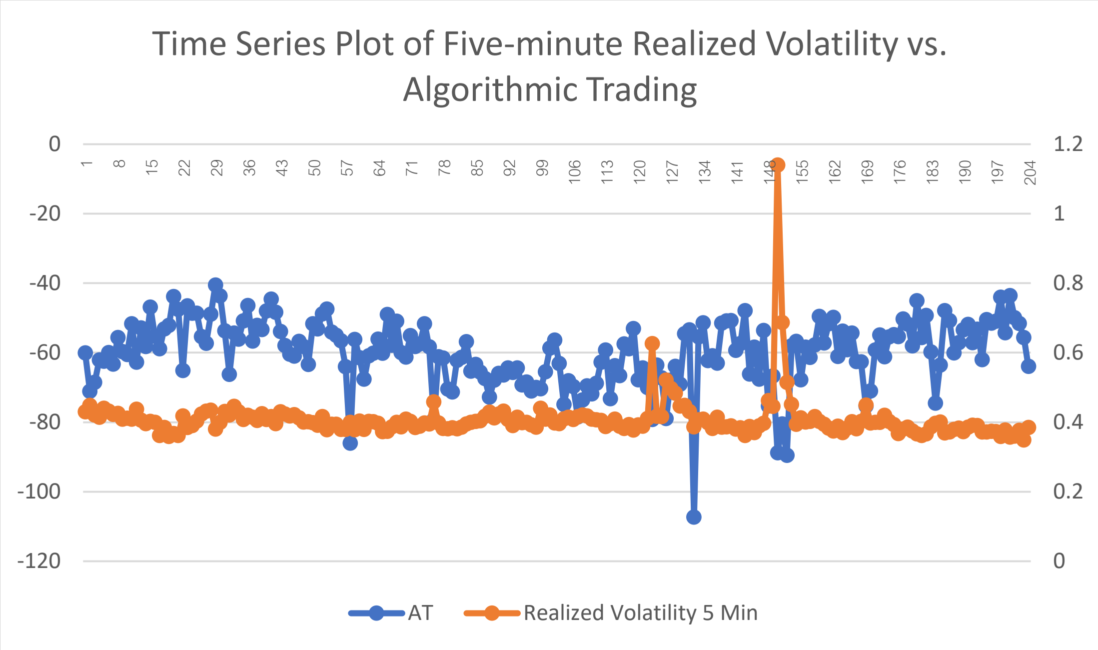

Figure 3.2 Time Series Plot of Five-minute Realized Volatility vs. Algorithmic Trading

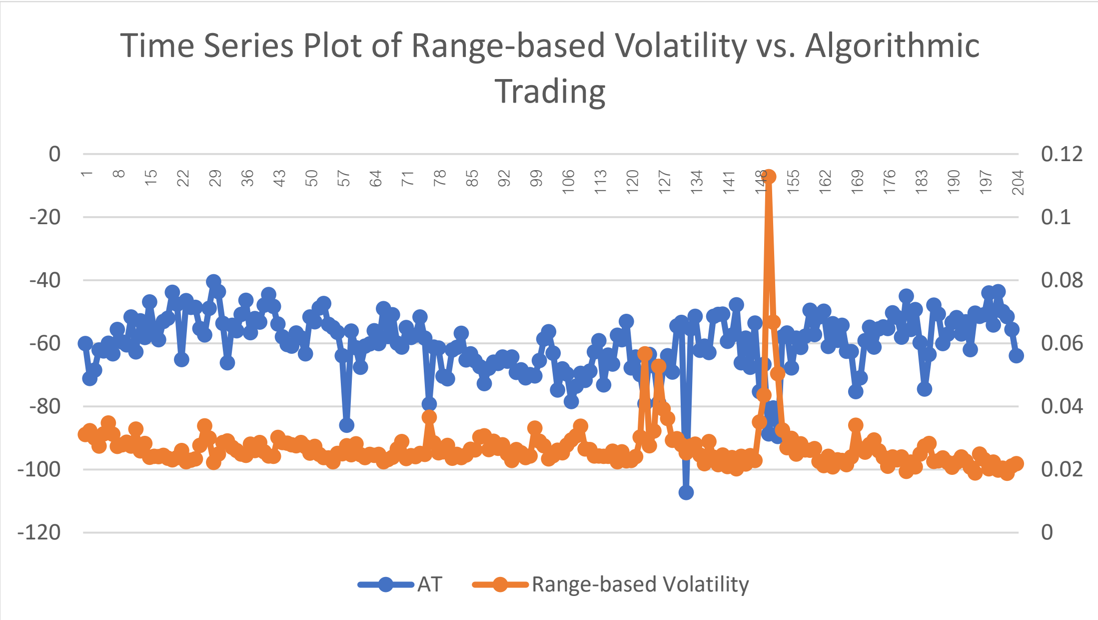

Figure 3.3 Time Series Plot of Range-based Volatility vs. Algorithmic Trading

For my sample, I defined the volatile market period as the month in which the market volatility is the highest. October 2016 is the volatile market period. Table 3.4

the summary statistics for the volatile period. The average values of one-minute and five-minute realized volatilities during the volatile market are 0.3100 and 0.4505 percent respectively. Range-based volatility during the volatile market is 0.0333. The average of the algorithmic trading proxy during the volatile period is -44.3094. Furthermore, the mean of the algorithmic trading initiated by institutional investors proxy during the volatile market is -103.3188. In addition, the algorithmic trading initiated by foreign investors proxy averages at -41.2547 during the volatile period. Table 3.4 reveals that the algorithmic trading proxy and the algorithmic trading initiated by foreign investors during the volatile period is lower than the ones during the entire sample. This indicates that the algorithmic trading activities and the algorithmic trading activities initiated by foreign investors activities are less active during the volatile period than during the entire period. This may assert that during the volatile period, algorithmic traders reduce their participation in the market.

Table 3.4 Summary Statistics for the Volatile Period

Variables	Mean	Median	Std. Dev.	Min.	Max.
Dependent Variables					
One-minute realized volatility (%)	0.3100	0.2813	0.1365	0.0838	2.3374
Five-minute realized volatility (%)	0.4505	0.4065	0.2335	0.1334	3.1380
Range-based volatility	0.0333	0.0252	0.0273	0.0031	0.2844
Independent Variables					
Algorithmic trading proxy (all)	-44.3094	-33.6595	37.6396	-262.8045	-2.1917
Algorithmic trading proxy (institutional investors)	-103.3188	-72.1200	99.2081	-707.6388	-0.0246

Table 3.4 (Continued)

Variables	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Algorithmic trading proxy (foreign investors)	-41.2547	-24.3944	46.3279	-455.7125	-0.0421
Stock Characteristics					
Ln(market_cap)	14.3197	14.1321	1.1080	12.2580	17.2062
Price-to-book ratio	3.5157	2.2500	3.7816	0.5800	26.8100
Share turnover	0.0049	0.0030	0.0062	6.76×10^{-5}	0.0716
The inverse of share price (1/Baht)	0.1047	0.0465	0.1387	0.0019	0.6785
Effective Half Spread (%)	0.2642	0.2392	0.1225	0.0684	0.7455

3.4 Results and Discussion

3.4.1 Correlation Analysis

3.4.1.1 All Periods

Table 3.5 reports the correlation matrix. All the variables exhibit significant correlations except the pair of the algorithmic trading initiated by foreign investor proxy and the price-to-book ratio. Noticeably, algorithmic trading is positively correlated with one-minute realized volatility ($r = 0.131$ and $p < 0.01$) and five-minute realized volatility ($r = 0.156$ and $p < 0.01$). The magnitude of correlation (r) increases when the sampling time for computing realized volatility increases. In contrast, range-based volatility exhibits a negative relationship with algorithmic trading ($r = 0.131$ and $p < 0.01$).

Consistent with the previous results, algorithmic trading initiated by institutional and foreign investors proxies have positive correlations with the one-minute and five-minute realized volatilities and a negative correlation with range-based volatility. The correlations between algorithmic trading initiated by institutional investors and realized volatilities using one-minute and five-minute sampling time are 0.064 *(p < 0.01)* and 0.118 *(p < 0.01)* respectively. The correlations between algorithmic trading initiated by foreign investors and realized volatilities using one-minute and five-minute sampling time are 0.105 *(p < 0.01)* and 0.154 *(p < 0.01)* respectively. Range-based volatility is negatively correlated with the algorithmic trading initiated by institutional investors proxy (r = -0.059 and p < 0.01) and the algorithmic trading initiated by foreign investors proxy (r = -0.022 and p < 0.01).

Table 3.5 Correlation matrix. *, ** and *** denote significance at the 10%, 5% and 1% level. **1** = 1-minute realized volatility, **2** = 5-minute realized volatility, **3** = range-based volatility, **4** = algorithmic trading proxy, **5** = algorithmic trading initiated by institutional investors, **6** = algorithmic trading initiated by foreign investors, **7** = the natural logarithmic of market capitalization, **8** = price-to-book ratio, **9** = share turnover, **10** = the inverse of price and **11** = effective half spread

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	1										
2	0.844***	1									
3	0.390***	0.610***	1								
4	0.131***	0.156***	-0.092***	1							
5	0.064***	0.118***	-0.059***	0.835***	1						
6	0.105***	0.154***	-0.022***	0.870***	0.666***	1					
7	-0.165***	-0.296***	-0.141***	-0.688***	-0.657***	-0.622***	1				
8	0.041***	0.068***	0.123***	-0.037***	-0.028***	0.004	0.056***	1			
9	0.271***	0.327***	0.532***	-0.257***	-0.243***	-0.225***	-0.118***	-0.035***	1		
10	0.217***	0.168***	-0.004***	0.306***	0.250***	0.215***	-0.346***	-0.119***	0.044***	1	
11	0.725***	0.537***	-0.051***	0.323***	0.242***	0.261***	-0.235***	-0.011	-0.101***	0.223***	1

From the correlation analysis, the correlation between algorithmic trading initiated by foreign investors and realized volatility is higher than the correlation between algorithmic trading initiated by institutional investors and realized volatility. On the contrary, the magnitude of the correlation between algorithmic trading initiated by institutional investors and range-based volatility is higher than that between algorithmic trading initiated by foreign investors and range-based volatility. Therefore, the correlation analysis alludes that algorithmic trading initiated by foreign investors has more effect in increasing realized volatility than algorithmic trading initiated by institutional investors does. However, algorithmic trading initiated by institutional investors has more effect in reducing range-based volatility than algorithmic trading initiated by foreign investors does.

The control variables have the same correlation directions as predicted, except for the correlation between the range-based volatility and the inverse of the average price and the correlation between the range-based volatility and the effective half spread. The natural logarithm of the market capitalization is negatively correlated with all volatility measures. Therefore, the larger the firm size, the smaller the volatility. Furthermore, all the algorithmic trading proxies indicate negative correlations with the natural logarithm of the market capitalization, implying that algorithmic trading is more likely to participate in the smaller firms. The correlation between the natural logarithm of market capitalization and various measures of the algorithmic trading proxies i.e. the algorithmic trading proxy, the algorithmic trading initiated by institutional investors proxy and the algorithmic trading initiated by foreign investors proxy are -0.688, -0.657 and -0.622 respectively, which are quite high. This may be subjected to the multicollinearity problems.

Volatility is higher in the firms with larger price-to-book ratio which is rational because if stocks are overvalued, volatility should be higher. It is interesting to note that the algorithmic trading proxy is negatively correlated with the price-to-book ratio and I found no correlation between algorithmic trading initiated by foreign investors and the price-to-book ratio.

As predicted, share turnover is positively correlated with volatility. In addition, the correlation between algorithmic trading and share turnover is small and negative ($r = -0.257$ and $p < 0.01$). The negative and small correlation between these two variables confirms that an increase in the algorithmic trading proxy using a normalized traffic message, is not due to an increase in trading volume.

The correlation between the inverse of the average price and realized volatility is positive while the correlation between the inverse of the average price and range-based volatility is negative. The inverse of average price is positively correlated with all three types of algorithmic trading proxies. Additionally, the correlation between effective spread and realized volatility is positive while the correlation between effective spread and range-based volatility is negative. Effective spread shows positive correlations with algorithmic trading proxies.

3.4.1.2 Volatile Period

Table 3.6 reports a correlation matrix during the volatile period. During the volatile period, the correlation between the algorithmic trading proxy and one-minute and five-minute realized volatility are 0.096 and 0.096 respectively. The correlation between the algorithmic trading initiated by institutional investors proxy and one-minute and five-minute realized volatilities are 0.064 and 0.067 respectively. Finally, the correlation between the algorithmic trading initiated by foreign investors proxy and one-minute and five-minute realized volatility are 0.062 and 0.077 respectively. The correlation between range-based volatility and the algorithmic trading proxy is -0.090 and the correlation between range-based volatility and the algorithmic trading initiated by institutional investors proxy is -0.056. The correlation between range-based volatility and the algorithmic trading initiated by foreign investors proxy is insignificant.

Conclusively, the correlations between all algorithmic trading proxies and all realized volatilities are higher during the entire period than during the volatile period. On the contrary, the correlation between range-based volatility and the algorithmic trading proxy is lower during the volatile period than during the entire period. Similarly, the correlation between range-based volatility and the algorithmic trading initiated by institutional investors proxy is lower during the volatile period than during the entire period.

The direction and the significance of the correlation between the control variables and the volatility measures remain unchanged except for two pairs of correlations. They are the correlation between range-based volatility and the inverse of price and the correlation between range-based volatility and effective half spread.

Table 3.6 Correlation Matrix during the Volatile period. *, ** and *** denote significance at the 10%, 5% and 1% level. 1 = 1-minute realized volatility, 2 = 5-minute realized volatility, 3 = range-based volatility, 4 = algorithmic trading proxy, 5 = algorithmic trading initiated by institutional investors, 6 = algorithmic trading initiated by foreign investors, 7 = the natural logarithmic of market capitalization, 8 = price-to-book ratio, 9 = share turnover, 10 = the inverse of price and 11 = effective half spread.

	1	2	3	4	5	6	7	8	9	10	11
1	1										
2	0.831***	1									
3	0.611***	0.811***	1								
4	0.096***	0.096***	-0.090***	1							
5	0.064***	0.067***	-0.056**	0.898***	1						
6	0.062***	0.077***	-0.030	0.861***	0.732***	1					
7	-0.136***	-0.226***	-0.164***	-0.704***	-0.687***	-0.666***	1				
8	0.089***	0.058**	0.095***	-0.022	-0.026	0.019	0.071***	1			
9	0.282***	0.344***	0.472***	-0.324***	-0.303	-0.228***	-0.086***	-0.037	1		
10	0.201***	0.133***	0.029	0.313***	0.266***	0.215***	-0.350***	-0.122***	0.061**	1	
11	0.637***	0.375***	-0.002	0.316***	0.254***	0.223***	-0.183***	0.038	-0.094***	0.228***	1

3.4.2 The Effect of Algorithmic Trading Proxy on Volatility

First, I estimated a multivariable regression using the pooled ordinary least square regression. There is no multicollinearity (See Appendix A-1). Table 3.7 summarizes the pooled OLS regression coefficients. The algorithmic trading proxy is positively associated with one-minute realized volatility (β_1 = 6.3215x10^{-5} and p < 0.01). One standard deviation increase in algorithmic trading, which is equivalent to 37.0363, leads to an increase in one-minute realized volatility by 6.3215x10^{-5} x 37.0363 = 0.0023 percent. As the mean value of one-minute realized volatility is equal to 0.2920 percent, algorithmic trading is associated with an increase in one-minute realized volatility by 0.8018 percent from its average.

However, the algorithmic trading proxy is negatively associated with the five-minute realized volatility (β_1 = -0.0001 and p < 0.01), which is inconsistent with the correlation result. This implies that when algorithmic trading increases by one standard deviation, five-minute realized volatility decreases by 0.0037 percent, which is equivalent to 0.9149 percent decline in five-minute realized volatility from its mean value.

Consistent with the correlation result, the algorithmic trading proxy has a negative relationship with range-based volatility (β_1 = -8.6620x10^{-6} and p = 0.043). Range-based volatility is decreased by 0.0003 percent for each additional standard deviation of algorithmic trading, which is equal to 1.2198 percent decrease from its corresponding average value.

Table 3.7 OLS Regression of Algorithmic Trading Proxy and Control Variables on Volatility Measures. *, ** and *** denote significance at the 10%, 5% and 1% level.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
Intercept	-0.0354***	0.4812***	0.0439***
	(-3.827)	(30.836)	(22.77)
AT_{it}	6.3215 x 10^{-5***}	-0.0001***	-8.6620 x 10^{-6**}
	(3.081)	(-3.342)	(-2.024)
Price-to-book ratio	0.0019***	0.0038***	0.0006***
	(14.312)	(16.564)	(22.718)
Share turnover	6.7606***	9.0740***	1.4403***
	(71.848)	(57.106)	(73.388)
The inverse of	0.0537***	4.3429 x 10^{-5}	-0.0050***
price	(14.099)	(0.007)	(-6.291)
Effective half	0.6446***	0.6275***	-0.0012
spread	(162.424)	(93.626)	(-1.505)
Natural log of	0.0079***	-0.0213***	-0.0018***
market cap	(11.925)	(-19.015)	(12.903)
Adjusted R^2	65.25%	45.87%	31.17%

Stock heterogeneity is an important source of variations in volatility measures. (See proof for heterogeneity in Appendix A-2). I conducted various tests to select the proper model. Appendix A-3 to A-4 provide the test results. I included the two-way fixed effects in the model and estimated the multivariate models using the within-group two-way fixed effects estimator (Appendix A-5 presents regression outcomes for other estimation methods).

Table 3.8 Within-group (Two ways) Fixed-effect Regression of Algorithmic Trading Proxy and Control Variables on Volatility Measures. *, ** and *** denote significance at the 10%, 5% and 1% level.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
AT_{it}	-1.3535x10^{-4}***	-0.0003***	-3.1443x10^{-5}***
	(-5.951)	(-8.197)	(-6.830)
Price-to-book ratio	0.0066***	0.0068***	0.0008***
	(12.120)	(7.694)	(7.370)
Share turnover	4.0987***	6.7096***	1.3644***
	(41.745)	(41.881)	(68.650)
The inverse of	-0.0155***	0.0786*	0.0184***
price	(-0.552)	(1.720)	(3.250)
Effective half	0.5338***	0.5106***	-0.0050***
spread	(125.943)	(73.829)	(-5.858)
Natural log of market cap			
Adjusted R^2	48.83%	28.45%	28.42%

From Table 3.8, the regression coefficients of the algorithmic trading proxy for the realized volatility models are negative, implying that when algorithmic trading increases, realized volatility decreases. When the algorithmic trading proxy increases by one standard deviation, one-minute realized volatility and the five-minute realized volatility are decrease by 0.0050 and 0.0111 percent or 1.7167 and 2.7448 percent from their associated mean values respectively. Moreover, range-based volatility is decreased by 0.0012 or 4.4279 percent from the mean value as algorithmic trading proxy enlarges by one standard deviation.

However, this negative relationship between algorithmic trading and realized volatility is inconsistent with the correlation result. This may be because there are some stocks with large variations in volatility, affecting the overall result. As a result, to remedy this inconsistency, I implemented the ordinary least square regression analysis for each stock. Appendix A-6 depicts the regression coefficients of the algorithmic trading proxy on the realized volatility models for each stock. Table 3.9 summarizes the regression coefficients.

Out of 91 stocks (I deleted all the stocks that were not listed in the SET100 for the entire year), forty-eight stocks have statistically significant relationships between algorithmic trading and one-minute realized volatility and forty-four stocks have statistically significant relationships between algorithmic trading and five-minute realized volatility.

Evidently, from Table 3.9, for the relationship between algorithmic trading and one-minute realized volatility, three-third of all the significant coefficients are positive with the average value of 0.0013 whereas the rest are negative with the mean of -0.0015. Therefore, algorithmic trading is mostly related to increasing volatility. However, when algorithmic trading reduces volatility, the effect is higher. Therefore, for most of the stocks, one standard deviation increase in algorithmic trading leads to 16.49 percent increase in one-minute realized volatility.

Table 3.9 Summary of OLS Regression of Volatility Measures on Algorithmic Trading Proxy and Control Variables for Each Stock.

	1-minute Realized Volatility	**5-minute Realized Volatility**
	Significant	
Number	48	44
	Positive and Significant	
Number	36	32
Average	0.0013	0.0018

Table 3.9 (Continued)

	1-minute Realized Volatility	5-minute Realized Volatility
	Negative and Significant	
Number	12	12
Average	-0.0015	-0.0025

For the relationship between algorithmic trading and five-minute realized volatility, about seventy-three percent of all the significant coefficients are positive with the average value of 0.0018. The positive effect of algorithmic trading on five-minute realized volatility is higher than the one on one-minute realized volatility. One standard deviation increase in algorithmic trading leads to 22.83 percent increase in five-minute realized volatility. The average coefficient for the negative relationship is -0.0025 which is higher than the positive relationship, confirming our assumption that the negative relationship between algorithmic trading and realized volatility is higher, and thus skew the within-effect regression results.

3.4.3 The Causal Relationship between Algorithmic Trading Proxy and Volatility

As the linear regression only establishes the relationship, in order to ascertain the causal relationships, which is essential for policy decisions, I conducted two additional estimation method and statistical analysis.

3.4.3.1 Two-stage Least Square Estimation

I conducted the two-stage least squares (2SLS) regression. The 2SLS regression coefficients are narrated in Table 3.10. I found that in the first stage regression, instrumental variable is related to algorithmic trading proxy ($\widehat{\beta_1} = 1.6585\ and\ p < 0.01$). In the second stage regression, all the regression coefficients for algorithmic trading proxies are statistically significant. Three outcomes can be drawn.

Firstly, the slope coefficient from the regression of algorithmic trading on one-minute realized volatility is -0.0038 with the confidence level of 99%. Therefore, algorithmic trading causes one-minute realized volatility to decrease. One standard deviation increase in algorithmic trading causes a decrease in one-minute realized volatility by 0.1396 percent, which is equivalent to 47.83 percent from the mean value.

Secondly, the slope coefficient of the algorithmic trading proxy on five-minute realized volatility is -0.0030 with the confidence level of 95%, which is slightly lower than the one on one-minute realized volatility. Consistent with the impact of algorithmic trading on one-minute realized volatility, algorithmic trading causes five-minute realized volatility to decrease. One standard deviation increase in algorithmic trading causes five-minute realized volatility to decrease by 0.1125 percent, which is equivalent to 27.79 decline from the mean value. Together, algorithmic trading causes realized volatility to decrease.

Table 3.10 2SLS Analysis for the Impact of Algorithmic Trading Proxy on Volatility Measures. *, ** and *** denote significance at the 10%, 5% and 1%.

Variable	First Stage Algorithmic Trading	Second Stage 1-min Realized Volatility	Second Stage 5-min Realized Volatility	Second Stage Range-based Volatility
Intercept	245.4933***	1.0274***	1.3638***	0.1709***
	(85.388)	(3.884)	(4.385)	(4.215)
Instrumental Variable	1.6585***			
	(3.930)			
Algorithmic trading		-3.7706x10^{-3***}	-3.0370x10^{-3**}	-4.1874x10^{-4**}
		(-3.511)	(-2.405)	(-2.544)
Inverse of price	13.7264***	0.1087***	0.0397**	0.0004
	(8.955)	(6.742)	(2.096)	(0.181)
Spread	47.1543***	0.7829***	0.7089***	0.0092
	(29.954)	(15.341)	(11.814)	(1.173)
Natural log of market cap	-21.1312***	-0.0782***	-0.0897***	-0.0115***
	(-111.560)	(-3.441)	(-3.358)	(-3.306)

Lastly, the regression coefficient of the algorithmic trading proxy on range-based volatility is -0.0004 with the confidence level of 95%. Similar to the previous results, the direction of the effect of algorithmic trading on range-based volatility is negative. Therefore, when algorithmic trading increases by one standard deviation, range-based volatility is decreased by 0.0155 percent or 58.97 percent from the mean value.

All in all, the regression coefficients estimated by the 2SLS regression have the same direction as the one estimated by the fixed-effects models. However, the magnitude of the coefficients estimated by 2SLS regression is higher than the one established by the fixed-effects models.

3.4.3.2 Granger Causality Test

The ordinary least square regression affirms the relationship between the algorithmic trading proxies and the volatility measures. In addition, to determine the causal relationship, I implemented the Granger Causality test (See Appendix A-7 for the stationary of the variables). The results from the Granger causality tests using the Dumitrescu-Hurlin framework are portrayed in Table 3.11. There are bilateral causal relationships between algorithmic trading and realized volatility sampling every one minute and five minutes. Similar result is established for the relationship between algorithmic trading and range-based volatility. Therefore, algorithmic trading granger causes one-minute realized volatility, five-minute realized volatility and range-based volatility to change. In turn, volatility measures also granger cause algorithmic trading activities to change, which corresponds to the literature review that algorithmic traders monitor the market volatility and adjust their trades accordingly. These results are also consistent with the results of the 2SLS regression analyses.

Table 3.11 Granger Causality Test of the Causal Relationship Between Algorithmic Trading Proxy and Volatility Measures

Direction of Causality	Ztilde Statistics	p-value	Decision
$RV_{i,t}^{1-min} \rightarrow AT_{i,t}$	9.7115	< 0.01	Reject
$AT_{i,t} \rightarrow RV_{i,t}^{1-min}$	4.6088	< 0.01	Reject
$RV_{i,t}^{5-min} \rightarrow AT_{i,t}$	7.2857	< 0.01	Reject
$AT_{i,t} \rightarrow RV_{i,t}^{5-min}$	3.7180	< 0.01	Reject
$RBV_{i,t} \rightarrow AT_{i,t}$	3.2447	< 0.01	Reject
$AT_{i,t} \rightarrow RBV_{i,t}$	4.4837	< 0.01	Reject

3.4.4 The Effect of Algorithmic Trading Proxy Initiated by Institutional and Foreign Investors on Volatility

Understanding the effect of algorithmic trading initiated by each types of investors is helpful for the regulators. This helps to determine the type of investors who implement algorithms that affects volatility. Does the algorithmic trading initiated by institutional or the algorithmic trading initiated by foreign investors destabilize the stock market? Therefore, in this section, I provided the fixed-effect regression results in Table 3.12. It yields the following results.

First, the effects of algorithmic trading initiated by institutional and foreign investors on one-minute realized volatility are negative. The effect of algorithmic trading initiated by institutional investors on one-minute realized volatility is more intense than the effect of algorithmic trading initiated by foreign investors on one-minute realized volatility. The regression coefficient of algorithmic trading initiated by institutional investors on one-minute realized volatility is -1.1491×10^{-4}, denoting that one-minute realized volatility is diminished by 0.0108 percent or 3.69 percent from the mean value due to one standard deviation increment in algorithmic trading initiated by institutional investors. Likewise, algorithmic trading initiated by foreign investors decreases one-minute realized volatility by 0.0085 percent or 2.90 percent from the mean value per each additional standard deviation of algorithmic trading initiated by foreign investors. The interaction term between two types of algorithmic trading proxies results in a decrease in one-minute realized volatility by 1.30 percent from the mean for each additional standard deviation increase in the interaction term between both types of the algorithmic trading proxies.

Second, the slope coefficients of the algorithmic trading initiated by institutional and foreign investors proxies and their interaction term in the second regression model are -1.9654 x 10^{-4}, -3.4470 x 10^{-4} and -1.3498 x 10^{-6} respectively. As a result, a change in one standard deviation in algorithmic trading initiated by institutional and foreign investors leads to a change in the five-minute realized volatility in a reverse direction by 4.55 percent and 4.15 percent from the mean values respectively. Aggregately, the interaction term between these two proxies results in a decrease in five-minute realized volatility by 1.52 percent from the mean value. Again, the effect of algorithmic trading initiated by institutional investors on five-minute realized volatility is more intense than the effect of algorithmic trading initiated by foreign investors on five-minute realized volatility.

Table 3.12 Two-way Within-group Regression of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables on Volatility Measures. *, ** and *** denote significance at the 10%, 5% and 1% level.

Variable	Model 1 1-minute Realized Volatility	Model 2 5-minute Realized Volatility	Model 3 Range-based Volatility
AT_I	$-1.1491x10^{-4***}$	$-1.9654x10^{-4***}$	$-1.0357x10^{-5***}$
	(-12.199)	(-12.797)	(-5.400)
AT_F	$-1.7384x10^{-4***}$	$-3.4470x10^{-4***}$	$-1.0963x10^{-5**}$
	(-8.086)	(-9.833)	(-2.504)
AT_IxAT_F	$-8.3305x10^{-7***}$	$-1.3498x10^{-6***}$	$-7.2880x10^{-8***}$
	(-11.934)	(-11.860)	(-5.127)

Table 3.12 (Continued)

Variable	Model 1 1-minute Realized Volatility	Model 2 5-minute Realized Volatility	Model 3 Range-based Volatility
Price-to-book ratio	0.0060***	0.0057***	0.0008***
	(10.976)	(6.343)	(7.017)
Share turnover	3.9427***	6.4397***	1.3962***
	(39.748)	(39.8159)	(69.123)
The inverse of price	0.0194	0.1260***	0.0225***
	(0.679)	(2.7033)	(3.859)
Effective half spread	0.5355***	0.5103***	-0.0059***
	(125.144)	(73.130)	(-6.764)
Natural log of market cap			
Adjusted R^2	48.91%	28.51%	28.33%

Third, corresponding to the previous result, the effect of algorithmic trading initiated by institutional and foreign investors proxies on range-based volatility are negative. One standard deviation increase in algorithmic trading initiated by institutional and foreign investors lead to declines in range-based volatility by 3.69 and 2.03 percent from the mean value respectively. Moreover, range-based volatility is also decreased by 1.27 percent from the mean value due to one standard deviation increase in the interaction term between algorithmic trading initiated by institutional and foreign investors. Similar to the previous result, algorithmic trading initiated by institutional investors contributes more in decreasing volatility than algorithmic trading initiated by foreign investors does.

Overall, algorithms initiated by institutional and foreign investors are beneficial to the market by reducing both realized volatility and range-based volatility. Furthermore, algorithmic trading initiated by institutional investors contributes more in lowering volatility than algorithmic trading initiated by foreign investors. However, the results for the effect of algorithmic trading initiated by each types of investors on realized volatility is inconsistent with the result from the correlation analysis. Like in previous section, there might be large variation in the data that might affect the overall result. Therefore, I separated the data to compute the regression analysis for each stock. Table 3.13 provides the summary of the result and appendix A-8 provides the detailed results.

Table 3.13 Summary of OLS Regression of Volatility Measures on Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables for Each Stock. AT_I is the algorithmic trading initiated by institutional investors proxy and AT_F is the algorithmic trading initiated by foreign investors proxy.

	AT_I	**AT_F**	**AT_I x AT_F**	**AT_I**	**AT_F**	**AT_I x AT_F**
	1-minute realized volatility			**5-minute realized volatility**		
	Significant coefficients					
Number	25	32	29	22	28	32
	Positive coefficients					
Number	9	15	2	5	11	2
Average	0.0044	0.0013	$1.8x10^{-5}$	0.00084	0.0013	$4.2x10^{-5}$
	Negative coefficients					
Number	16	17	27	17	17	30
Average	$-3.4x10^{-4}$	$-7.2x10^{-4}$	$-8.7x10^{-6}$	-0.0006	-0.0017	$-1.5x10^{-5}$

Out of 91 stocks, I discovered that twenty-five of all stocks have a significant relationship between the algorithmic trading initiated by institutional investors proxy and one-minute realized volatility. Nine of which have positive coefficients with the average of 0.0044 and the rest have negative coefficients with the average of -0.00034. Thirty-two of all stocks have a significant relationship between the algorithmic trading initiated by foreign investors proxy and one-minute realized volatility where fifteen of them are positively related with the average of 0.0013 and the rest are negatively related with the average of -0.00072. Twenty-nine of the interaction terms are significant. Almost all these variables are negative with the average coefficient of $-8.7x10^{-6}$.

Out of 91 stocks, twenty-two of them have significant relationships between the algorithmic trading initiated by institutional investors proxy and five-minute realized volatility, twenty-eight of them have significant relationships between the algorithmic trading initiated by foreign investors proxy and five-minute realized volatility and thirty-two of them have significant relationships between the interaction term and five-minute realized volatility. The majority of the coefficients are negative. Therefore, it is conclusive that algorithmic trading initiated by institutional and foreign investors have negative relationships with one-minute and five-minute realized volatility.

3.4.5 The Effect of Algorithmic Trading Proxy on Volatility during the Volatile Market

To understand the role of algorithmic traders on volatility during the volatile market period, I conducted the within-group two-way fixed-effect regression analysis using the October sample (See multicollinearity problem test, heterogeneity test, model selection test and regression coefficients of estimation methods in Appendix A-9 to A-13).

From Table 3.14, similar to the coefficient estimated by the pooled OLS method, the regression coefficients of algorithmic trading on one-minute and the five-minute realized volatility are insignificant. Therefore, this assures that there is no relationship between the algorithmic trading proxy and realized volatility during the volatile period. Hence, algorithmic trading is not associated with realized volatility during the volatile period.

On the other hand, the regression coefficient of the algorithmic trading proxy on the range-based volatility is significantly negative which is -0.00005. Hence, when the algorithmic trading proxy increases by one standard deviation, range-based volatility is decreased by 0.0019 or 5.70% from the mean value.

Table 3.14 Two-Way Within-group Fixed-effect Regression of Algorithmic Trading Proxy and Control Variables on Volatility Measures during the Volatile Period. *, ** and *** denote significance at the 10%, 5% and 1% level.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
AT_{it}	$-5.7738\text{x}10^{-5}$	$-1.0705\text{x}10^{-4}$	$-5.0449\text{x}10^{-5**}$
	(-0.500)	(-0.496)	(-1.977)
Price-to-book ratio	-0.0068	0.0019	-0.0021
	(-1.155)	(0.172)	(-1.630)
Share turnover	3.3853***	7.2396***	1.5400***
	(6.770)	(7.744)	(13.928)
The inverse of	0.3570	0.9352*	0.1974***
price	(1.193)	(1.672)	(2.984)
Effective half	0.5970***	0.6205***	0.0134***
spread	(27.055)	(15.044)	(2.750)
Adjusted R^2	27.24%	9.06%	8.79%

3.4.6 The Causal Relationship between Algorithmic Trading Proxy and Volatility during the Volatile Period

I utilized the Granger causality test to assess the causal relationship between algorithmic trading and volatility during the volatile period. Analogous to the previous section, the volatile period is during October. I utilized the sample from October 2016 which is defined as the volatile period to determine the causal relationship between algorithmic trading proxy and volatility measures. All variables during the volatile period are stationary (See Appendix A-14). The Granger causality test results are depicted in Table 3.15 using the Dumitrescu-Hurlin's method and show that there is no causal relationship between algorithmic trading and volatility measures.

Table 3.15 Granger Causality Test of the Causal Relationship between Algorithmic Trading and Volatility Measures during the Volatile Period

Direction of Causality	Ztilde Statistics	p-value	Decision
$RV_{i,t}^{1-min} \rightarrow AT_{i,t}$	1.1443	0.2525	Fail to reject
$AT_{i,t} \rightarrow RV_{i,t}^{1-min}$	-1.1279	0.2594	Fail to reject
$RV_{i,t}^{5-min} \rightarrow AT_{i,t}$	1.0942	0.2739	Fail to reject
$AT_{i,t} \rightarrow RV_{i,t}^{5-min}$	-1.2236	0.2173	Fail to reject
$RBV_{i,t} \rightarrow AT_{i,t}$	-0.9726	0.3308	Fail to reject
$AT_{i,t} \rightarrow RBV_{i,t}$	0.5483	0.5835	Fail to reject

3.4.7 The Effect of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies on Volatility during the Volatile Markets

The algorithmic trading initiated by institutional and foreign investors enable us to probe into the effect of algorithmic trading initiated by each type of market participants on volatility during the volatile period. This allows us to investigate which type of investors lessens or enlarges volatility. Therefore, I estimated the regression analysis using the two-way within-group fixed-effect models as depicted in Table 3.16. Appendix A-15 shows the regression coefficient estimated by OLS.

Evidently, during the volatile period, there are negative relationships between algorithmic trading proxies and both types of realized volatility. In particular, the algorithmic trading initiated by institutional investors proxy is associated with negative change in one minute and five-minute realized volatility by 0.0145 and 0.0283 percent respectively, which are equal to 4.67 and 6.28 percent from the average values for every additional standard deviation increase in the algorithmic trading initiated by institutional investors proxy. Furthermore, one standard deviation increase in algorithmic trading initiated by foreign investors lowers one-minute and five-minute realized volatility by 0.0163 and 0.0348 percent respectively. They are equal to 5.26 and 7.73 percent change from the mean value. Together, the interaction term between algorithmic trading initiated by institutional and foreign investors decreases one-minute and five-minute realized volatility by 0.0065 and 0.0123 percent or 2.10 and 2.73 percent from their averages respectively. There is no evidence of the relationship between the algorithmic trading proxies and range-based volatility.

Table 3.16 Two-way Within-group Fixed-effect Regression of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables on Volatility Measures during the Volatile Period.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
AT_I	-1.4590×10^{-4}***	-2.8539×10^{-4}***	-6.7525×10^{-6}
	(-3.205)	(-3.351)	(-0.666)
AT_F	-3.5189×10^{-4}***	-7.5201×10^{-4}***	-3.6305×10^{-5}
	(-3.411)	(-3.897)	(-1.580)
AT_I x AT_F	-1.4193×10^{-6}***	-2.6758×10^{-6}***	-2.6966×10^{-8}
	(-4.375)	(-4.409)	(-0.373)
Price-to-book ratio	-0.0072	0.0005	-0.0019
	(-1.216)	(0.042)	(-1.468)
Share turnover	2.9443***	6.2141***	1.5447***
	(6.022)	(6.793)	(14.179)
The inverse of price	0.3641	1.0061*	0.2044***
	(1.210)	(1.787)	(3.050)
Effective half spread	0.6105***	0.6503***	0.0140***
	(27.359)	(15.577)	(2.807)
Adjusted R^2	27.86%	10.01%	8.62%

Note: *, ** and *** denote significance at the 10%, 5% and 1% level.

All in all, the effect of algorithmic trading initiated by foreign investors is stronger than the one initiated by institutional investors during the volatile period. Furthermore, the effects of algorithmic trading initiated by both investors are stronger during the volatile market than during the entire period. Therefore, during volatile period, algorithmic trading initiated by both investors help to lessen realized volatility; but have no effects on range-based volatility.

3.5 Conclusion

The benefits and the detriments of the algorithmic trading activity on volatility are widely debated and the empirical results are mixed. The rise in volatility increases risk in the market. Therefore, the effect of algorithmic trading on volatility is of interest to policymakers and investors. Using a SET100 transaction and order submission dataset, I analyzed the effect of algorithmic trading on return volatility. I used a normalized message traffic which is the negative ratio of trading volume to the total number of all message traffic. I exploited various estimation techniques to estimate and establish the relationship between algorithmic trading and volatility. It yields six important outcomes:

First, algorithmic trading decreases volatility i.e. realized volatility and range-based volatility. Using the correlation analysis, there is a positive relationship between all types of algorithmic trading proxies and realized volatility and a negative relationship between all types of algorithmic trading proxies and range-based volatility. However, conducting two-way fixed-effect regression analysis reveals that on average, algorithmic trading decreases realized volatility as much as 2.74 percent from its average while decreases range-based volatility by 4.43 percent from its mean. Delving further, I investigated the regression analysis for each stock and showed that most of the significant regression coefficients are positive, revealing that algorithmic trading increases volatility, but the magnitude of the negative regression coefficients is higher than that of the positive regression coefficients. Individually, algorithmic trading mostly increases volatility, but on aggregate, algorithmic trading lowers volatility.

Second, there is a causal relationship between algorithmic trading proxy and volatility measures i.e. one-minute realized volatility, five-minute realized volatility and range-based volatility as verified by the 2SLS regression and Granger causality test. From 2SLS analysis, one standard deviation increase in the algorithmic trading proxy causes decreases in one-minute realized volatility, five-minute realized volatility and range-based volatility by 47.83, 27.79 and 58.97 percent from their average values respectively.

Third, algorithmic trading initiated by institutional and foreign investors and their interaction term lower realized volatility and range-based volatility. Using the two-way fixed-effect model, one standard deviation increase in algorithmic trading initiated by institutional investors reduces one-minute realized volatility by 3.69 percent from its mean, five-minute realized volatility by 4.55 percent from its mean and range-based volatility by 3.69 percent from its mean. Similarly, one standard deviation increase in algorithmic trading initiated by foreign investors lowers one-minute and five minute realized volatility and range-based volatility by 2.90, 4.15 and 2.03 percent from their associated means respectively. Along the same line but with smaller magnitude, the interaction term also lowers one-minute and five-minute realized volatility by 1.30 and 1.52 percent from their mean values respectively and decreases range-based volatility by 1.27 percent from its average value. Clearly, the magnitude of the effect associated with algorithmic trading initiated by institutional investors is higher than that of foreign investors. Furthermore, using separate OLS regression, the negative relationship between algorithmic trading and realized volatility is also established.

Fourth, during the volatile period there is no relationship between algorithmic trading and realized volatility, however, algorithmic trading decreases range-based volatility by 5.70 percent from its mean value during that period. The effect of algorithmic trading on range-based volatility is higher during the volatile period than during the entire sample.

Fifth, I found no evidence of the causal relationships between algorithmic trading and volatility measures during the volatile period. On the other word, algorithmic trading does not Granger cause volatility during the volatile period and volatility does not Granger cause algorithmic trading activities to change during the volatile period.

Lastly, during the volatile period, algorithmic trading initiated by foreign investors plays more roles in lowering realized volatility than algorithmic trading initiated by institutional investors does. Furthermore, the effects of algorithmic trading initiated by both types of investors during the volatile period are stronger than the ones during the entire period. There is no evidence of the relationship between algorithmic trading initiated by institutional and foreign investors and range-based volatility.

All in all, algorithmic trading causes volatility to decrease. Our result is consistent with the results by Westerholm (2016), Hagströmer and Nordén (2013), Brogaard (2011), Chaboud, Chiquoine, Hjalmarsson, and Vega (2014). I showed that volatility causes algorithmic trading to change and in return, algorithmic trading causes volatility to decrease. This indicates that algorithmic traders monitor market and respond accordingly. This result is emphasized when I analyzed the effect of algorithmic trading separated by type of investors. This shows that algorithmic traders help to reduce volatility, indicating that algorithmic traders act like informed investors in lowering volatility. The use of technology in making trading decisions and submitting orders does not change the behavior of institutional and foreign investors as informed traders.

Furthermore, during the entire period, algorithmic trading initiated by institutional investors contributes more in reducing volatility than algorithmic trading initiated by foreign investors do. This indicates that algorithms implemented by institutional investors help to dampen volatility. However, the role is switched during the volatile period. Algorithmic trading initiated by foreign investors helps to dampen realized volatility more than algorithmic trading initiated by institutional investors does. From this empirical study, I showed that algorithmic traders still act like informed investors and are beneficial for the market. Moreover, algorithmic traders are not responsible for an increase in volatility during the volatile period.

CHAPTER 4

THE IMPACT OF ALGORITHMIC TRADING ON LIQUIDITY

4.1 Introduction

Investors invest their wealth into assets. When they want to access their wealth, liquid markets enable them to convert assets into wealth promptly and at a minimal cost. Therefore, liquidity helps to foster investment, enabling firms and economies to grow. Stock exchanges, thus, have a role in supplying liquidity to their market participants. Firms with liquid stocks perform better (Fang, Noe, & Tice, 2009). Brogaard, Li, and Xia (2017) found that liquid stocks reduce default risk. A decrease in liquidity poses liquidity risk to investors, reduces market efficiency and increases market fragility (Price Water-house Coopers: PwC, 2015). Market crashes occur due to a lack of liquidity supply when there is liquidity demand. Therefore, liquidity is an important determinant for market quality. O' Hara (2003) claimed that liquidity and price discovery are the cornerstone for market efficiency. Liquidity is related to price efficiency because if the market is not liquid, a buy or sell order will push the price upward or downward respectively

Liquid assets are the assets in which there are willing sellers and buyers, just below or just above the trading prices in order to trade assets continuously; and they allow large transactions to occur immediately, without affecting the underlying asset prices and the transaction costs. Alternatively, illiquid assets result in price deviation because sell or buy orders will force the prices to go up or down. In an extreme illiquidity, the gap between bid and ask spread is too costly to trade, resulting in market freezes. This is a typical scenario during a financial crisis.

Algorithmic traders are both passive liquidity suppliers and active liquidity demanders and lead to drastic changes in market microstructure. Followings are the features of algorithmic trading which help to facilitate and deter stock liquidity. First, one of the types of algorithmic traders is market-making high frequency traders. Their role is to provide liquidity to the market. Therefore, the participation of market-making high frequency traders increases competition in the market and therefore, reduces the costs to the intermediaries. When the immediacy supply increases, liquidity is improved. Second, though market-making high frequency traders supply liquidity to the market, their market participation is noncompulsory. Therefore, the liquidity can dry up when needed, worsening liquidity in the market. Third, for the agency algorithmic traders and other types of proprietary HFT, they consume liquidity by submitting market orders when they dissolve their positions or execute their trading strategies.

Fourth, algorithmic traders are able to monitor the market very closely, reducing monitoring cost. The low cost of monitoring empowers algorithmic traders to search for arbitrage opportunities and detect price anomality more efficiently with the lightning speed. In addition, algorithmic traders can adjust their orders to get ahead of the competitors. While this mitigates the adverse selection risks for the algorithmic traders, this may be at the disadvantages of the high latency traders. The informational advantages of algorithmic traders may increase the adverse selection costs of the high latency traders. Therefore, it discourages slower traders from participation, causing overinvestment in algorithmic trading technologies and rising systematic risk. Therefore, this characteristic of algorithmic traders might reduce liquidity. Fifth, Menkveld (2013) investigated the behavior of high frequency market makers and showed that their positions at the end of the day often resulted in net zero. This should help to reduce their inventory holding costs and thus lessen adverse selection problem for the algorithmic traders which results in increased liquidity.

Sixth, many researches showed that algorithmic trading is associated with fleeting order, which is the type of orders that gets cancelled within short period after submission. Therefore, liquidity provided by algorithmic traders might be illusionary. Lastly, high frequency traders, a subset of algorithmic traders, may have lower transaction costs due to their large trading volume.

Whether or not algorithmic trading advocates or deters liquidity depends on the aggregate effects of the interactions between algorithmic traders and other type of investors. As algorithmic trading strategies are mixed, their impacts on liquidity are varied depending on the strategies, and theories can only explain the impact on liquidity based on certain assumptions and strategies. Therefore, empirical study is required to explore the aggregate impact of algorithmic trading on liquidity.

In an emerging market, algorithmic trading has been gaining its importance. Hence, it is important to investigate the effect of algorithmic trading on liquidity – an important attribute of the market quality. As a result, our research questions become:

RQ# 1: What is the effect of algorithmic trading on liquidity?

RQ# 2: Is there a causal relationship between algorithmic trading and liquidity?

RQ# 3: What is the effect of algorithmic trading initiated by institutional and foreign investors on liquidity?

RQ# 4: What is the effect of algorithmic trading on liquidity during the volatile period?

RQ# 5: What are the effects of algorithmic trading initiated by each type of investors on liquidity during the volatile period?

4.2 Literature Review

4.2.1 Liquidity

Trading emerges due to the interaction between two types of investors: liquidity providers and liquidity demanders. Liquidity providers buy at a bid price or sell at an offer price whereas liquidity demanders buy at the offer price and sell at the bid price. Liquidity depends on the number of informed investors, their levels of risk aversions and the accuracy of their information (Subrahmanyan, 1991). Liquidity is an important issue as it represents the cost for liquidity demanders and the profit for liquidity providers.

Moreover, liquidity and illiquidity affect stock returns and asset price. Various researchers study the effect of liquidity on asset prices. O' Hara (1995) provided the theoretical framework while Hasbrouck (2007) provided the empirical works. Amihud and Mendelson (1986) demonstrated a positive relationship between the quoted bid-ask spreads and stock returns. There is a relationship between excess return or risk premium and illiquidity (Amihud & Mendelson, 1986). Furthermore, they found that there is a negative relationship between share turnover and illiquidity cost. Holden, Jacobsen, and Subrahmanyam (2014) found that liquidity is positively related to trading volume, price, political stability and accounting standard, negatively related to volatility and firm size. It is also related to season, economic cycle and around macroeconomic announcement.

Illiquidity is the impact of orders on prices (Kyle, 1985; Amihud, 2002). It happens when there is a large excess demand (Kraus & Stoll, 1972) and the market makers set the price in response of block trades which may be the result of informed trading (Easley & O' Hara, 1987). Market imperfection causes illiquidity. Vayanos and Wang (2011) summarized that there are six imperfections, namely, participation costs, transaction costs, asymmetric information, imperfection competition, funding constraints and search. Participation costs is the costs of entering the trade. Demsetz (1968) proposed that the role of market makers is in providing liquidity and the compensation for market markets is the bid-ask spread. Huang, Wong, Zhang, Shu, and Lam (2009) developed an equilibrium model to show that the participation cost causes temporary order imbalances, creating the need for liquidity. Illiquidity leads asset prices to be inefficient. In the worst case, this may lead to market crashes.

Transaction costs are the costs of executing orders such as brokerage commission, exchange fees, price impact, transaction taxes and bid-ask spread. Transaction costs are important for designing optimal investment (Constantides, 1986). Jang, Keun Koo, Liu, and Loewenstein (2007) demonstrated that transaction costs have the effect on liquidity premia. Furthermore, Lo, Mamaysky, and Wang (2004) showed that the transaction costs affect the asset price.

Asymmetric information arises because different traders have different sets of information. Those who receive private information demand liquidity. Grossman and Stiglitz (1980) provided the theoretical framework that is informed investors must be compensated for the cost of information gathering. When trading with better-informed investors, traders experience information asymmetry. Easley and O' Hara (2004) provided the theoretical model that the risk premium is affected by information asymmetry. If information is symmetry among agents, the price will be equal to its expected future value. However, with the presence of information asymmetry, the risk premium is positive. Therefore, investors require higher stock return in order to compensate for their risks when trading against better-informed investors. Copeland

and Galai (1983) presented the theory that market makers set bid-ask spreads to compensate for the information asymmetry costs.

In the perfect competition markets, all agents are equal, and no one can influence the prices. In actuality, some agents are larger than others in term of size or informational advantages. Therefore, their trades can have the effect on the prices. Vayanos and Wang (2011) showed that the expected return is lower when there is imperfect competition. Another important illiquidity source is the fund constraints. Brunnermeier and Pedersen (2008) showed that when liquidity suppliers have limited funds to take their positions, this decreases market liquidity. Lastly, search is when the counterparties need to find each other and negotiate in order for the trades to occur. Duffie (2010) showed that search delays affect asset prices and liquidity.

4.2.2 Measurement of Liquidity

Liquidity is a multi-dimensional concept. Liquid assets feature five characteristics: immediacy, depth, resilience, breadth and tightness (Dong, Kemph, & Yadav, 2007). Immediacy is the ability to execute the orders immediately at the desired price. Depth is the ability to execute the order without altering the prices. Market is deep when there are large numbers of orders on both bids and offers in a continuous basis. Market depth is related to high trading volume, low price impact of large orders and low volatility. Market resiliency is the speed for the prices to be resilient when there are random mispricing shocks. So that, the market prices reflect fundamental values and the trading processes do not affect the market prices (Hasbrouck, 2007). Breadth is when there are many market participants, and no one can cause significant price impact. Tightness is the transaction cost or the ability to sell and buy assets at approximately the same price when executed at the same time.

Liquidity measurement can be characterized into four categories: transaction cost measures, volume-based measures, equilibrium price-based measures and market-impact measures. There are two types of transaction costs: explicit costs, which are the direct costs associated with order processing, and implicit costs, which are the indirect costs. High transaction costs reduce the number of active market participants, affecting both breath and resiliency. Small number of participants prevent prices from correcting themselves to their fundamental levels.

Bid-ask spread is an important proxy for liquidity. Bid-ask spread is the difference between the highest quoted price that the buyers are willing to pay and the lowest quoted price that the sellers are willing to sell for a reference period. Bid-ask spread can also be calculated as percent spread. Effective spread is the midpoint of the bid and ask quotes minus the actual transaction price. Narrow effective spread indicates high liquidity. The pattern of bid-ask spread can be a good indicator of resiliency (Fleming & Sarkar, 1999).

To calculate bid-ask spread using non-intraday data, there are two type of models: serial covariance properties of the transaction prices (Roll 1984, Stoll 1989, Huang & Stoll 1997) and trade initiation indicator variable (Glosten & Harris 1988). Roll (1984) found that spreads are negative serial dependence of the transaction prices. Thus, there is a relationship between bid-ask spread and transaction price. Besides order processing costs, bid-ask spread incorporates two other costs, namely, inventory cost (Ho & Stoll, 1981) and adverse selection costs (Copeland & Galai,1983; Glosten & Milgrom, 1985). On the other word, spread is composed of two components: gain to the liquidity providers (measured by realized spread) and loss to the liquidity consumers (measured by adverse selection). Inventory component is the cost associated with holding nonzero positions at the end of the day and adverse selection component is the cost associated with trading with informed investors. The inventory component and order-processing fee is the gross-profit component for market makers (Cohen, Maier, Schwartz, & Whitcomb, 1979; Amihud & Mendelson, 1986; Ho & Stoll, 1981; Glosten, 1987) whereas bid-ask spread is the compensation for the information trade and the profit for the liquidity trade for liquidity providers.

The adverse selection component is because the better-informed investors possess superior private information. When trading with better informed investors, investors or market makers face adverse selection risks, and thus, set the spread to compensate for this risk. This adverse selection component is correlated with the efficient price and the magnitude of the covariance is related to the size of asymmetric information (Glosten, 1987).

According to Glosten (1987), the bid (B) and ask (A) prices can be expressed as:

$$A = a(A) + C_A = p + Z_A + C_A$$
$$B = b(B) - C_B = p - Z_B - C_B$$

where H is the public information, Z_A and Z_B are the adverse selection component of the bid-ask spread and C_A and C_B are the gross profit component of the bid-ask spread which includes transaction costs and inventory costs. p is the transaction cost, which can be expressed as:

$$p = E[p^*|H],$$

p^* is the prices which fully incorporates all information and $a(x)$ is the expectation function of which the market maker sets to incorporate all public information when investor buys at x and $b(y)$ is the expectation function of which the market maker sets to incorporate all public information when investor sells at y which can be expressed as:

$$a(x) = E[p^*|H, investor\ buys\ at\ x],$$
$$b(y) = E[p^*|H, investor\ buys\ at\ y].$$

With this definition, the transaction price ($\hat{p}_n$) can be expressed as

$$\hat{p}_n = p_n + C_n Q_n.$$

The quoted spread is equal to $Z_A + Z_B + C_A + C_B$.

Volume-based measure uses volume traded to determine liquidity. Common indicators are trading volume, turnover rate, volatility of share turnover and Hui-Heubel ratio. Trading volume is the sum of the products of prices and quantities traded and share turnover is the ratio of trading volume to the outstanding stock volume. Hui-Heubel ratio is the ratio of percentage change in the prices during five-day period to the ratio of volume traded to the outstanding volume. Volume-based measure is associated with breath dimension of liquidity. Furthermore, size or market value is associated with liquidity as larger stocks have lower price impact and lower bid-ask spread (Fama & French, 1992).

Price impact can be measured by various methods: the illiquidity ratio (Amihud, 2002), the Kyle (1985)'s price impact (λ) and the fixed-cost component of the bid-ask spread (ψ), the probability of information-based trading (Easley, Kiefer, O', Hara, & Paperman, 1996) and the transaction-by-transaction price response to signed order size (Brennan & Subrahmanyam, 1996). The probability of information-based trading represents the level of information asymmetry and the adverse selection cost.

Evaluating only transaction cost and volumes as measures for liquidity can be misleading. When there is new information, new equilibrium prices can be reached. Small volume can lead to large price changes. In liquid or resilient markets, prices are continuous. To understand security liquidity, one must be able to distinguish between short-term and long-term price changes. Therefore, there are ways to calculate short-term price changes that are not caused by changes in fundamental values, such as market efficient coefficient (Hasbrouck & Schwartz, 1988), which calculates short-term price changes from long-term price changes, price impact measures and econometric techniques such as vector autoregression lags of price adjustment, autoregressive moving average (ARMA) of volumes traded, autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models.

4.2.3 Theories of the Effect of Algorithmic Trading on Liquidity

Algorithmic trading employs both liquidity-demanding and liquidity-supplying strategies. It possesses many features that elicits liquidity, namely, the participation costs, transaction costs, asymmetric information, more competitive markets and search. Algorithmic trading can use their automated information-retrieving system and high-speed order submissions to closely watch the market information and modify their orders accordingly. Liquidity suppliers increase liquidity but may crowd out other traders. On the other hand, liquidity demanders reduce liquidity (Hasbrouck & Saar, 2013) and increase adverse selection costs onto other traders (Hagströmer & Nordén, 2013, Biais, Foucoult, & Moinas, 2015). In addition, algorithmic traders have no obligations in providing liquidity when required, thus, the liquidity provided by them can be evaporated when needed.

The effect of AT on liquidity depends on the type of algorithm trading. Bongaerts and van Achter (2012) presented the model of the interaction between algorithmic trading and slower investors and showed that the probability for the orders submitted by slower investors to be matched is reduced when algorithmic traders are present. Guibaud and Pham (2013) constructed the model for the limit order book to determine the effect of market-making HFT on liquidity and showed that algorithmic traders can reduce the inventory risk. Foucault, Hombert and Roşu (2016) provided the model mimicking the traders' behaviors upon the arrival of news. They predicted that high-frequency trading improves liquidity. As high frequency traders engage in zero net positions at the end of the days, their inventory holding costs are reduced (Menkveld, 2013; Menkveld, 2014). Additionally, Roseman (2015) showed that fleeting orders have little impact on liquidity and represent noise to the market.

Many theoretical framework studies the impact of algorithmic trading on liquidity. Biais et al. (2015) modelled the equilibrium of different latency traders to determine their effects on liquidity component, in particular, on the adverse selection costs. They showed that low-latency traders impose adverse selection costs onto other traders, increasing negative externalities. Jovanovic and Menkveld (2016) analyzed the effect of high frequency trading on adverse selection costs by modelling the role of high frequency traders on the limit order book and revealed that high frequency trading reduces adverse selection cost.

4.2.4 Empirical Studies of the Effect of Algorithmic Trading on Liquidity

A number of theoretical models and empirical researches on the effect of algorithmic trading on liquidity were conducted. While the results of the theoretical models can only explain the impact of algorithmic trading on liquidity due to certain assumptions, the empirical findings are ambiguous. In some markets, researchers found that algorithmic trading advocates liquidity and in other markets, algorithmic trading deteriorates liquidity. This may be because algorithmic trading strategies are heterogeneous, and thus, their impacts of liquidity are mixed. Furthermore, most of the researches were conducted in developed and fragmented markets. Due to differences in market structures and trading volume, it is interesting to explore the impact of algorithmic trading on liquidity in an emerging market.

Multiple empirical studies investigated the relationship between algorithmic trading and liquidity using various types of studies and methodology. Types of studies include single market and multiple markets studies and the methodology used are panel data analysis, instrumental variables and event studies.

On the NASDAQ-OMX Stockholm index, Hagströmer and Nörden (2013) investigated the limit orders submitted by high frequency traders. In their sample, they found that 71.5% of the orders submitted are market-making. Furthermore, they showed that market-making HFTs participate more in the stocks which have high trading volume and large bid-ask spread; and are large market-cap stocks and less volatile. Hendershott and Riordan (2013) exploited the data of the 30 Deutscher Aktien Index stocks on the Deutsche Boerse to study the effect of algorithmic traders on supplying and demanding liquidity. They found that algorithmic traders demanded liquidity when it was cheap and supplied it when it was expensive. Zhang and Riordan (2011) utilized the data from the stocks listed in NASDAQ with the identification of the transactions whether they were executed by high frequency traders. Correspondingly, they found a similar result which is most of high frequency traders are market makers who provide liquidity when the spread is tight and supply it when the spread is wide. In the same stock exchange, Carrion (2013) utilized the data set with the identification of twenty-six high frequency trader accounts. He found similar result which was that high frequency traders provide liquidity when the spread is wide and consume it when the reverse is true.

Many researches confirm a positive relationship between algorithmic trading and liquidity. On the effect of algorithmic trading on bid-ask spread, Hasbrouck and Saar (2013) utilized the same dataset, but with different HFT identification approach. They found that high frequency trading lowers quoted and effective spread and augments order depth. Hendershott et al. (2011) introduced a new method, a normalized message traffic, to measure algorithmic trading activities. They used the introduction of autoquote as an instrument variable to provide the causal relationship between algorithmic trading and liquidity and showed that algorithmic trading causes an increase in liquidity and a decrease in adverse selection cost in the NYSE stocks especially for the large market capitalization stocks. Brogaard, Hagströmer, Nordén, and Riordan (2015) examined the event of the co-location update which reduced the execution speed. They showed that traders especially co-located traders use the faster speed to reduce their adverse selection costs. This thus helps to improve the bid-ask spread and the market depth. On the same note, Riordan and Storkenmaier (2012) used the reduction in market latency in the Deutsche Boerse exchange as an instrumental variable and showed that the quoted spread is reduced by 0.86 bps through lowering the adverse selection costs. Malinova, Park, and Riordan (2018) explored whether how the high frequency traders affect the retail traders. Using the change in the regulatory fees in Canada, they discovered that the change in the fee reduces the high frequency traders' activities and increases the spread. The reduction in the algorithmic trading activities has a negative impact on other traders. Jovanovic and Menkveld (2016) warned that the reduction in bid-ask spread as witnessed in many empirical studies caused by high frequency trading may be due to high frequency trading snipping, and thus, it does not represent an improvement in market quality.

In addition to the equity markets, Viljoen, Westerholm, and Zheng (2014) investigated the effect of algorithmic trading on liquidity in the SPI 200 futures and revealed that algorithmic trading reduces effective spread and increases realized spreads by lowering adverse selection cost. Chaboud et al. (2014) examined the foreign exchange markets. They found that algorithmic trading fosters liquidity in the market by providing liquidity when there is a demand for it and consuming it when the arbitrage opportunity arises. Furthermore, they pass on adverse selection risks to high-latency traders.

Other researchers conducted the studies using multiple market dataset. First was Menkveld (2013) who obtained the data from the Chi-X and the Euronext which were the Dutch index stocks. Menkveld (2013) found that high frequency trading increases the trading activities in Chi-X and facilitates liquidity in Chi-X such that it contributes to the success of the Chi-X index in the initial phase. On the international markets, Boehmer et al. (2015) showed that algorithmic trading ameliorates liquidity.

In some markets, algorithmic trading or high frequency trading leads to deterred liquidity. Hendershott and Moulton (2011) found that high frequency traders leads to larger quoted spreads as a result of increased adverse selection cost by using the latency reduction in the NYSE's Hybrid market as an instrumental variable. van Ness, van Ness, and Watson (2015) used the dataset of the NASDAQ-listed and the NYSE-listed stocks and reported that an increase in the cancellation rate of the limit orders increases effective and realized spreads and price impact while decreases the depth and the size of the limit order book. Furthermore, Upson and van Ness (2017) presented that algorithmic trading reduces the National Best Bid and Offer (NBBO) depth for the NYSE stocks. Additionally, Cartea, Payne, Penalva, and Tapia (2019) exhibited that the ultra-fast activity is associated with enlarged quoted and effective spreads and reduced depth on NASDAQ. Similarly, Manahov (2016) conducted an experimental research and found that HFT imposes adverse selection cost onto informed investors and they, therefore, incorporate that risk by requiring higher bid-ask spreads.

Furthermore, in some markets, there is no relationship between algorithmic trading and liquidity. Ye, Yao, and Gai (2013) documented no relationship between liquidity and speed of trading in the NASDAQ stock as a result of tick size reduction. Brogaard et al. (2012) also found no relationship between AT and liquidity in the FTSE250 index.

During the market distress, Hasbrouck and Saar (2013) studied the event of economic turmoil in 2008 and showed that algorithmic trading increases liquidity by decreasing spread and improving depth. Nawn and Banerjee (2018) utilized the data from the National Stock Exchange of India and revealed that algorithmic traders increase their limit order book supply and improve liquidity in market during the period of high volatility.

4.3 Sample and Methodology

4.3.1 Algorithmic Trading Measurement

As the data obtained from the Stock Exchange of Thailand database does not identify algorithmic traders, following Hendershott et al. (2011), I used a normalized message traffic as a proxy of algorithmic trading. Thereby, the daily algorithmic trading proxy is measured by:

$$AT_{it} = \frac{-V_{it}}{MT_{it}} \tag{4.1}$$

where AT_{it} is algorithmic trading associated with stock *i* on day *t*, V_{it} is the trading volume of stock *i* on day *t* and MT_{it} is the message traffic of stock *i* on day *t*. Message traffic is defined as all order submissions (buy, sell and revision), cancellations and trade reports.

Furthermore, the monthly algorithmic trading proxy is measured by:

$$AT_{im} = \frac{-V_{im}}{MT_{im}} \tag{4.2}$$

where AT_{im} is algorithmic trading associated with stock *i* on month *m*, V_{im} is the trading volume of stock *i* on month *m* and MT_{im} is the message traffic of stock *i* on month *m*.

4.3.2 Liquidity Measurement

The data from the Stock Exchange of Thailand does not record the price revisions, thus limit order book cannot be constructed properly. Therefore, in order to measure liquidity, I found an alternative measurement by inferring liquidity measures from transaction prices.

4.3.2.1 Effective Bid-ask Spread ($ESPREAD$)

I measured an effective bid-ask spread using the Roll's spread estimator. It can be measured by:

$$s = 2\sqrt{-Cov(\Delta p_t, \Delta p_{t+1})} \tag{4.3}$$

where s is the effective half bid-ask spread and p is the transaction price. (See the derivation of this equation in Appendix B-1). The higher the effective bid-ask spread, the lower the liquidity of the stock.

4.3.2.2 Share Turnover ($TURNOVER$)

Besides the bid-ask spread, I employed volume-based measures to explore other dimension of liquidity. This method has been used widely in many research papers (Brennan & Subrahmanyam, 1996; Marshall & Young, 2003; Korajczyk & Sadka, 2008). In our case, I used the share turnover which is the ratio of the volume of the shares traded to the outstanding stocks.

$$TURNOVER_{it} = \frac{VOL_{it}}{N_{it}} \tag{4.4}$$

where VOL_{it} is the trading volume in baht and N_{it} is the outstanding stocks for stock i on time t. Share turnover is the proxy for stock liquidity. High share turnover implies that there are large number of stocks available to trade. Low share turnover implies that the asset is less liquid and there is a small number of stocks available to trade, causing difficulties to the investors to liquidate their assets. Therefore, the level of share turnover is positively related to the level of stock liquidity. In addition, Chae (2005) associated the trading volume with the level of information asymmetry. Therefore, the level of share turnover represents the level of information asymmetry in the market (Copeland & Galai, 1983; Bartov & Bodnar, 1996).

4.3.2.3 The Amihud Estimate ($ILLIQ$)

Amihud (2002) proposed the illiquidity measure as the average of the daily ratio of the absolute value of the stock return to the trading volume.

$$ILLIQ_{im} = \frac{1}{D_{im}} \sum_{t=1}^{D_{im}} \frac{|R_{imd}|}{VOL_{imd}} \tag{4.5}$$

where R_{imd} is the stock return, VOL_{imd} is the trading volume in baht for stock i on day d of month m and D_{im} is the number of trading day for stock i on month m. It is a rough estimate of price impact as it represents the change in price in response to one unit change in trading volume.

4.3.2.4 Liquidity Ratio (LR)

Amivest liquidity ratio measures liquidity by determining the tolerance level in which large trading volume can be traded without changing the price level. Therefore, liquidity ratio is defined as:

$$LR_{im} = \frac{\sum_{t=1}^{D_{im}} VOL_{imd}}{\sum_{t=1}^{D_{im}} |R_{imd}|} \tag{4.6}$$

where R_{imd} is the stock return, VOL_{imd} is the trading volume in baht for stock *i* on day *d* of month *m* and D_{im} is the number of trading day for stock *i* on month *m*. Amihud, Mendelson, and Lauterbach (1997) showed that liquidity ratio is associated with the market depth. The higher the liquidity ratio is, the more liquidity or depth the stock is because liquid stock can execute large amount of trading volume without prices being changed. This is also associated with the information asymmetry level.

4.3.3 Control Variables

To isolate the effect of algorithmic trading on liquidity, I included control variables, which are the variables that affect liquidity. They are the realized volatility, the natural logarithmic value of the market capitalization, the inverse of average price and the share turnover. As volatility is associated with liquidity due to its effect on inventory risk, volatility is included in the control variable (Chordia, Roll, & Subrahmanyam, 2001). Zhang et al. (2008) and Wang and Yau (2000) found a positive relationship between bid-ask spread and volatility. Realized volatility can be computed by the following formula:

$$RV_{it} = \sqrt{\frac{\sum_{t=1}^{d}(R_{it} - \bar{R})^2}{d-1}} \quad (4.7)$$

where RV_{it} is the realized volatility (the frequency of data sampling is five minutes), R_{it} is the stock return sampling every five minute, $\bar{R}$ is the mean stock return and d is the number of periods during the measured time.

Audretsch and Elston (2002) suggested that firm size has the effect on liquidity. However, the research conducted by Brockman and Chung (2002) did not find the relationship between firm size and liquidity. Roll (1984) suggested that as firm size is related to volume and volume is negatively related to spread, firm size is negatively associated with spread. Furthermore, studies showed that higher trading volume is associated with better liquidity (Kim & Verrecchia, 1994). Furthermore, I used the inverse of price as a proxy for transaction cost and tick size. Tick size has a negative effect on liquidity; or the smaller the tick size, the more liquid the stocks (Ahn, Cai, Chan, & Hamao, 2007). Similarly, MacKinnon and Nemiroff (2014) investigated the decimalization of the Toronto Stock Exchange and disclosed that the bid-ask spread is reduced upon the decimalization while there is no effect on price impact.

4.3.4 Model Specification

4.3.4.1 Linear Regression Model

I established the model for the relationship between algorithmic trading and liquidity. The algorithmic trading proxy is an independent variable and the control variables are included in the models in order to avoid confounding effects. Therefore, the daily liquidity models become:

$$ESPREAD_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + \varepsilon_{it} \quad (4.8)$$

$$TURNOVER_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (4.9)$$

The monthly liquidity models can then be expressed as:

$$ILLIQ_{im} = \alpha + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + \varepsilon_{im} \quad (4.10)$$

$$LR_{im} = \alpha + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + \varepsilon_{im} \quad (4.11)$$

The description of dependent and independent variables is listed on Table 4.1.

Table 4.1 Description of the Variables

Variables	Description
Dependent	
ESPREAD	Effective spread, estimated by Roll's estimation
ILLIQ	The Amihud illiquidity estimate, measuring illiquidity
LR	Liquidity ratio
Independent	
AT	Algorithmic trading. The negative ratio of the volume traded to the traffic messages
VOLATILITY	Daily realized volatility with the sampling frequency of 5 minute
PRICE	The daily average price traded
MARKET CAP	Market capitalization is the total market value of the company's outstanding shares
Dependent and Independent	
TURNOVER	Share turnover is the total number of shares traded by the average number of shares outstanding over a period

The multiple regression analysis is used to test the following null hypothesis which states that there is no relationship between algorithmic trading and liquidity:

H_0: β_1 = 0

H_1: β_1 is not equal to 0.

Multicollinearity problem may cause the estimated regression coefficient β_1 to be unreliable because it has large standard errors. This happens when the predictor variables are highly correlated. I employed the variance inflation factor (VIF) to detect it. If each score is more than five, that variable suffers from multicollinearity problem.

Literature review yields mixed results for the effect of algorithmic trading on liquidity; in other words, it may increase or decrease liquidity. The automated trading by algorithmic traders can provide liquidity by decreasing monitoring cost. At the same time, the rise of robotic or algorithmic trading worries high-latency traders. Trading with fast and informed investors may increase information asymmetry and thus, increase adverse selection cost. As adverse selection cost is a component in liquidity, this, thus decreases liquidity. Furthermore, as the majority of the trading activities in the Stock Exchange of Thailand is still primarily submitted by humans and algorithmic trading in Thailand is growing and often executed by informed investors, its role in providing liquidity may be inadequate, comparing to its influence on other traders. Therefore, I hypothesized that there is a negative relationship between algorithmic trading and liquidity.

The ordinary least squares model assumes that there is no heterogeneity in the variables. To assess whether there is heterogeneity in the data, I plotted the mean across individual and the mean across time. To alleviate the heterogeneity in the panel data, I estimated six alternative estimation techniques which were pooled ordinary least square, individual fixed effects, time fixed effects, two-way fixed effects, individual random effects and time random effects models. The daily liquidity within-group fixed-effects models are shown below:

$$\begin{aligned} ESPREAD_{\imath t} = \beta_1 AT_{\imath t} + \beta_2 VOLATILITY_{\imath t} + \beta_3 \left(\frac{1}{PRICE}\right)_{\imath t} \\ + \beta_4 LN(MARKET\ CAP)_{\imath t} + \beta_5 TURNOVER_{\imath t} + \varepsilon_{it} \end{aligned} \tag{4.12}$$

$$\begin{aligned} TURNOVER_{\imath t} = \alpha + \beta_1 AT_{\imath t} + \beta_2 VOLATILITY_{\imath t} + \beta_3 \left(\frac{1}{PRICE}\right)_{\imath t} \\ + \beta_4 \overline{LN(MARKET\ CAP)_{\imath t}} + \varepsilon_{it} \end{aligned} \tag{4.13}$$

where $ESPREAD_{\imath t}$, $TURNOVER_{\imath t}$, $AT_{\imath t}$, $VOLATILITY_{\imath t}$, $\left(\frac{1}{PRICE}\right)_{\imath t}$ and $LN(MARKET\ CAP)_{\imath t}$ are the mean-corrected values for the effective spread, the share turnover, the algorithmic trading proxy, volatility, the inverse of average price and the natural logarithmic of market capitalization for stock i on day t. Additionally, the model for monthly variables are:

$$ILLIQ_{\imath m} = \alpha + \beta_1 AT_{\imath m} + \beta_2 VOLATILITY_{\imath m} + \beta_3 \left(\frac{1}{PRICE}\right)_{\imath m} + \beta_4 LN(MARKET\ CAP)_{\imath m} + \beta_5 TURNOVER_{\imath m} + \varepsilon_{im} \quad (4.14)$$

$$LR_{\imath m} = \alpha + \beta_1 AT_{\imath m} + \beta_2 VOLATILITY_{\imath m} + \beta_3 \left(\frac{1}{PRICE}\right)_{\imath m} + \beta_4 LN(MARKET\ CAP)_{\imath m} + \beta_5 TURNOVER_{im} + \varepsilon_{im} \quad (4.15)$$

where $ILLIQ_{\imath m}$, $LR_{\imath m}$, $AT_{\imath m}$, $VOLATILITY_{\imath m}$, $\left(\frac{1}{PRICE}\right)_{\imath m}$, $LN(MARKET\ CAP)_{\imath m}$ and $TURNOVER_{\imath m}$ are the mean-corrected values for the Amihud illiquidity estimate, the liquidity ratio, the algorithmic trading proxy, the volatility, the inverse of average price, the natural logarithmic of market capitalization and the share turnover for stock i on month m. I conducted the individual, time and two-way fixed-effects model.

The random effects models can be expressed as:

$$ESPREAD_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + w_{it} \quad (4.16)$$

$$TURNOVER_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + w_{it} \quad (4.17)$$

$$ILLIQ_{im} = \alpha + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + w_{im} \quad (4.18)$$

$$LR_{im} = \alpha + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + w_{im} \quad (4.19)$$

where

$$w_{it} = \varepsilon_i + u_{it} \quad (4.20)$$

$$w_{im} = \varepsilon_i + u_{im} \quad (4.21)$$

w_{it} and w_{im} are the composite error terms, composing of two components: the individual-specific error component (ε_i) and the idiosyncratic term (u_{it} or u_{im}) which combine both individual and time error components.

The restricted F-test and the Hausman test are used to determine the estimation technique. The restricted F-test allows us to choose between the pooled OLS models and the fixed-effects models whereas the Hausman test is used to choose between the fixed-effects and the random effects models. The models for the restricted F-tests are shown below:

$$ESPREAD_{it} = \alpha_1 + \alpha_2 D_{2i} + \cdots + \alpha_n D_{ni} + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + \varepsilon_{it} \quad (4.22)$$

$$TURNOVER_{it} = \alpha_1 + \alpha_2 D_{2i} + \cdots + \alpha_n D_{ni} + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (4.23)$$

$$ILLIQ_{im} = \alpha_1 + \alpha_2 D_{2i} + \cdots + \alpha_n D_{ni} + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + \varepsilon_{im} \quad (4.24)$$

$$LR_{im} = \alpha_1 + \alpha_2 D_{2i} + \cdots + \alpha_n D_{ni} + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + \varepsilon_{im} \quad (4.25)$$

where $D_{2i} = 1$ for stock 2 and zero otherwise and $D_{ni} = 1$ for stock n and zero otherwise. The null hypothesis for these models is that the differential intercepts are equal to zero.

H_0: $\alpha_i = 0$ *for* $\forall\ i = 2, \ldots, n$

H_a: *At least one* α_i *is not equal to 0.*

4.3.4.2 Two-stage Least Squares Estimation

Hendershott and Riordan (2013) revealed that algorithmic trading and liquidity are endogenous variables. They showed that algorithmic traders closely watch the market. They supply liquidity when the spread is narrow and demand it when the spread is large. In addition, algorithmic traders may adjust their positions according to stock liquidity. Therefore, liquidity measures are endogenous variables.

To ascertain whether algorithmic trading has a causal effect on liquidity and to decipher possible endogeneity, the two-stage least squares estimation method is applied. This estimation method requires a proper instrumental variable (IV_{it}). I instrumented the event in October 2016 when there is an evidence of algorithmic traders' participation and the market experienced a flash crash. Therefore, a dummy variable is introduced which is equal to 1 after October 2016.

The first stage regression can be expressed as:

$$\widehat{AT}_{it} = \alpha + \beta_1 IV_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \mu_{it}. \quad (4.26)$$

$$\widehat{AT}_{im} = \alpha + \beta_1 IV_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \mu_{im}. \quad (4.27)$$

In the second stage regression, the effect of algorithmic trading on liquidity model can be estimated using the following equation:

$$ESPREAD_{it} = \alpha + \beta_1 \widehat{AT}_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \mu_{it} \quad (4.28)$$

$$TURNOVER_{it} = \alpha + \beta_1 \widehat{AT}_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \mu_{it} \quad (4.29)$$

$$ILLIQ_{im} = \alpha + \beta_1 \widehat{AT}_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + \mu_{im} \quad (4.30)$$

$$LR_{im} = \alpha + \beta_1 \widehat{AT}_{it} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \beta_5 TURNOVER_{im} + \mu_{im} \quad (4.31)$$

4.3.4.3 The Volatile Market

To examine how does the algorithmic traders provide or consume liquidity during the volatile market, I conducted the regression analysis during the volatile market. Table 4.2 illustrates the monthly SET index volatility. From the table, October 2016 is obviously the most volatile period.

Table 4.2 Monthly SET Index Volatility

Month	SET Index Volatility
March 2016	0.8039%
April 2016	0.8723%
May 2016	0.6041%
June 2016	0.7320%
July 2016	0.4541%
August 2016	0.5886%
September 2016	1.1805%
October 2016	1.4559%
November 2016	0.6617%
December 2016	0.4423%

Therefore, to evaluate whether algorithmic trading increases or decreases liquidity during the volatile period, I applied the following models to test the null hypothesis.

$$ESPREAD_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + \varepsilon_{it} \quad (4.32)$$

$$TURNOVER_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (4.33)$$

The models are to test the null hypothesis which is there is no relationship between algorithmic trading and liquidity:

H_0: β_1 = 0

H_a: β_1 is not equal to 0.

Similar to the earlier methods, I used the pooled OLS model, the fixed effects models and the random effects models to test the null hypothesis for all liquidity models. Then, the restricted F-test and the Hausman test are used to select the proper models. Furthermore, the Granger causality test is conducted to determine the causal relationship between algorithmic trading and liquidity during the volatile period.

4.3.5 Model Extension

In order to solve the third and the fifth research questions, I introduced the algorithmic trading initiated by institutional and foreign investors proxies. The daily algorithmic trading initiated by institutional investors proxy is calculated as:

$$AT_{it}^{I} = \frac{-V_{it}^{I}}{MT_{it}^{I}} \tag{4.34}$$

And, the daily algorithmic trading initiated by foreign investors proxy is measured as:

$$AT_{it}^{F} = \frac{-V_{it}^{F}}{MT_{it}^{F}} \tag{4.35}$$

where AT_{it}^{I} and AT_{it}^{F} are the proxies for the algorithmic trading initiated by institutional and foreign investors respectively. V_{it}^{I} and V_{it}^{F} are the trading volumes in Thai Baht initiated by institutional and foreign investors respectively. MT_{it}^{I} and MT_{it}^{F} are the message traffic for stock i on day t initiated by institutional and foreign investors respectively.

The monthly proxies of the algorithmic trading initiated by institutional investors and the algorithmic trading initiated by foreign investors are defined as following:

$$AT_{im}^{I} = \frac{-V_{im}^{I}}{MT_{im}^{I}} \tag{4.36}$$

$$AT_{im}^{F} = \frac{-V_{im}^{F}}{MT_{im}^{F}} \tag{4.37}$$

where AT_{im}^{I} and AT_{im}^{F} are the monthly proxies of algorithmic trading initiated by institutional and foreign investors respectively. V_{im}^{I} and V_{im}^{F} are the trading volumes initiated by institutional and foreign investors respectively in Thai Baht for stock i during the month m. MT_{im}^{I} and MT_{im}^{F} are the message traffic initiated by institutional and foreign investors respectively for stock i on month m.

As algorithmic trading initiated by institutional and foreign investors occur during the same period, I incorporated the algorithmic trading initiated by institutional investors proxy, the algorithmic trading initiated by foreign investors and their interaction term in the Equation 4.8 to 4.11. I included the interaction term in the model because it represents the effect of the trading between algorithmic trading initiated by two types of investors. Hence, the multivariate regression models can be written as:

$$ESPREAD_{it} = \alpha + \beta_1 AT_{it}^{I} + \beta_2 AT_{it}^{F} + \beta_3 AT_{it}^{I} x AT_{it}^{F} + \beta_4 VOLATILITY_{it} + \beta_5 \left(\frac{1}{PRICE}\right)_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \beta_7 TURNOVER_{it} + \varepsilon_{it} \quad (4.38)$$

$$TURNOVER_{it} = \alpha + \beta_1 AT_{it}^{I} + \beta_2 AT_{it}^{F} + \beta_3 AT_{it}^{I} x AT_{it}^{F} + \beta_4 VOLATILITY_{it} + \beta_5 \left(\frac{1}{PRICE}\right)_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \quad (4.39)$$

$$ILLIQ_{im} = \alpha + \beta_1 AT_{im}^{I} + \beta_2 AT_{im}^{F} + \beta_3 AT_{im}^{I} x AT_{im}^{F} + \beta_4 VOLATILITY_{im} + \beta_5 \left(\frac{1}{PRICE}\right)_{im} + \beta_6 LN(MARKET\ CAP)_{im} + \beta_7 TURNOVER_{im} + \varepsilon_{im} \quad (4.40)$$

$$LR_{im} = \alpha + \beta_1 AT_{im}^{I} + \beta_2 AT_{im}^{F} + \beta_3 AT_{im}^{I} x AT_{im}^{F} + \beta_4 VOLATILITY_{im} + \beta_5 \left(\frac{1}{PRICE}\right)_{im} + \beta_6 LN(MARKET\ CAP)_{im} + \beta_7 TURNOVER_{im} + \varepsilon_{im} \quad (4.41)$$

I used the same estimation analysis as the Section 4.3.4 to test the following null hypothesis.

H_0: β_1 = 0

H_a: β_1 is not equal to 0.

These regressions may be subjected to heterogeneity. The panel data analysis is used to eliminate heterogeneity problem. Therefore, I estimated these regression models using the pooled OLS, the fixed-effect model and the random-effects models. The restricted F-test and the Hausman test are used to determine the proper estimation method.

4.3.6 Descriptive Statistics

I eliminated all the stocks with incomplete data and eliminated the 2.5% outliers. The descriptive statistics is shown in Table 4.3. I separated the variables into three groups: daily, monthly and stock-specific. For the daily variables, they are effective half spread, daily share turnover, daily algorithmic trading proxy, daily algorithmic trading initiated by institutional investors proxy, daily algorithmic trading initiated by foreign investors proxy, and daily realized volatility computed using five-minute returns. The effective half spread has the average of 0.2759 percent and the daily share turnover has the average of 0.0044 or 0.44 percent of the total shares. The intraday realized volatility averages at 0.4087 percent. The algorithmic trading activity proxy averages at -38.7619 with the standard deviation of 28.7851. Clearly, the average algorithmic trading initiated by institutional investors proxy is lower than the average algorithmic trading initiated by foreign investors proxy. The mean value of the algorithmic trading proxy initiated by institutional investors proxy is **-**92**.**0656 with the standard deviation of 81.5097 whereas the mean value of the algorithmic trading initiated by foreign investors proxy is **-**36**.**6396 with the standard deviation of 38.7142.

The monthly variables consist of the Amihud's illiquidity estimate, the liquidity ratio, the monthly share turnover, the monthly algorithmic trading proxy, the monthly algorithmic trading initiated by institutional investors proxy, the monthly algorithmic trading initiated by foreign investors proxy and the monthly realized volatility computed using five-minute returns. The mean values of the Amihud's illiquidity estimate, the liquidity ratio and the monthly share turnover are 0.0192, 280.48 and 0.3979 or 39.79 percent respectively. The monthly realized volatility averages at 1.93%. The monthly algorithmic trading proxy has the average of -42.9421 with the standard deviation of 32.6008. Similar to the daily variables, the average value of the monthly algorithmic trading originated by institutional investors proxy is less than the average value of the monthly algorithmic trading originated by foreign investors proxy. The average value of the AT initiated by institutional investors proxy is -92.0656 with the standard deviation of 81.5097; and the average value of the AT initiated by foreign investors proxy is -36.6396 with the standard deviation of 38.7142.

The market capitalizations for SET100 stocks range from 6.81 to 959.55 billion baht. The daily return has the average of 0.03% and the daily trading volume has the average of 358.8 million baht with the peak at 11.2 billion baht.

Table 4.3 Descriptive Statistics

Variables	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Daily Variables					
Effective half spread (%)	0.2759	0.2520	0.1285	0.0000	1.1958
Share turnover	0.0044	0.0026	0.0057	0.0001	0.1246
Algorithmic trading proxy (all)	-38.7619	-30.3100	28.7851	-144.2637	-1.9105
Algorithmic trading proxy (institutional investors)	-92.0656	-68.1706	81.5097	-762.6927	-0.0047
Algorithmic trading proxy (foreign investors)	-36.6396	-23.0723	38.7142	-405.3131	-0.0071
Realized volatility (%)	0.4087	0.3909	0.1475	0.0000	3.1380
Monthly Variables					
Amihud's illiquidity estimate	0.0192	0.0101	0.0397	0.0004	0.8656
Liquidity ratio	280.4793	111.5262	394.6456	1.7731	2693.34
Share turnover	0.3979	0.0635	8.3270	0.0037	258.4999
Algorithmic trading proxy (all)	-42.9421	-33.3656	32.6008	-234.4509	-4.8512
Algorithmic trading proxy (institutional investors)	-101.3831	-79.0505	79.6619	-406.4480	-1.0932
Algorithmic trading proxy (foreign investors)	-38.9102	-25.7074	39.1597	-270.8551	-0.7577
Realized volatility (%)	1.9288	1.7901	0.8583	0.2876	11.6012

Table 4.3 (Continued)

Variables	Mean	Median	Std. Dev.	Min.	Max.
Stock Characteristics					
Market capitalization (billion Baht)	50.56	43.56	151.45	6.81	959.55
The inverse of share price (1/Baht)	0.1053	0.0464	0.1374	0.0019	0.6824
Daily return (%)	0.03	0.00	2.13	-59.32	33.91
Daily trading volume (million Baht)	358.81	136.55	611.41	0.20	11,282.35

In order to comprehend the role of algorithmic traders on liquidity during the volatile market, I examined the effect of algorithmic trading on liquidity during the volatile market, which is defined as during October 2016. The summary statistics shows the mean, the median, the standard deviation, the minimum and the maximum values of major variables during that period. The effective half spread averages at 0.2674 percent while the share turnover has the mean value of 0.0048. The average algorithmic trading proxy during the volatile period is lower than the average during the entire sample. The algorithmic trading proxy has the mean value at -40.1379 and the standard deviation at 29.0123. Similar to the previous result, the algorithmic trading initiated by foreign investors proxy is higher than the one initiated by institutional investors. The algorithmic trading by institutional investors proxy averages at -93.6519 with the standard deviation of 81.8384. The algorithmic trading initiated by foreign investors proxy averages at -36.5425 with the standard deviation of 36.4103.

For the monthly variables, the average values for Amihud's illiquidity estimate and liquidity ratio are 0.0184 and 281.56 respectively. The Amihud's illiquidity estimate for the volatile period is lower than the one for the entire period while the liquidity ratio is higher during the volatile period than during the entire period. Therefore, on average, the monthly liquidity is higher during the volatile period than during the entire period. The algorithmic trading proxy averages at -45.7550 with the standard deviation of 35.1765 which is lower than the one during the entire period. This suggests that algorithmic traders are less likely to participate in the market when the market becomes volatile. The algorithmic trading initiated by institutional investors proxy has the mean of -108.7213 with the standard deviation of 88.2576. On the other hand, the algorithmic trading initiated by foreign investors proxy has the average of -39.7478 and the standard deviation of 38.9824. The average of the algorithmic trading initiated by foreign investors proxy is higher than the average of the algorithmic trading initiated by institutional investors proxy, suggesting that foreign investors are more likely to utilize algorithmic strategies to trade.

Table 4.4 Descriptive Statistics for the Volatile Period

Variables	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Daily Variables					
Effective half spread (%)	0.2674	0.2431	0.1226	0.0684	0.7455
Share turnover	0.0048	0.0030	0.0059	6.76×10^{-5}	0.0598
Algorithmic trading proxy (all)	-40.1379	-32.4577	29.0123	-143.7478	-2.1917
Algorithmic trading proxy (institutional investors)	-93.6519	-63.2992	81.8384	-472.4223	-0.0246
Algorithmic trading proxy (foreign investors)	-36.5425	-23.5708	36.4103	-266.9184	-0.0421
Monthly Variables					
Amihud's illiquidity estimate	0.0184	0.0112	0.0219	0.0005	0.1074
Liquidity ratio	281.56	99.13	432.54	10.55	2317.78
Share turnover	0.1577	0.0724	0.4906	0.0151	4.7682

Table 4.4 (Continued)

Variables	Mean	Median	Std. Dev.	Min.	Max.
Algorithmic trading proxy (all)	-45.7750	-36.9929	35.1765	-174.4360	-8.6505
Algorithmic trading proxy (institutional investors)	-108.7213	-83.8841	88.2576	-398.8738	-9.5412
Algorithmic trading proxy (foreign investors)	-39.7478	-25.7979	38.9824	-186.0657	-2.4508
Realized volatility (%)	2.5990	2.4934	1.1540	0.8747	5.2344
Stock Characteristics					
Ln (market capitalization)	14.2509	14.1140	1.0454	12.2580	17.2062
The inverse of share price (1/Baht)	0.1076	0.0481	0.1398	0.0019	0.6785
Monthly return (%)	0.4535	0.4102	0.2348	0.1334	3.1380

4.4 Results and Discussion

4.4.1 Correlation Analysis

4.4.1.1 Entire Period

1) Daily Variable

The results of the Pearson correlation for the daily variables as depicted in Table 4.5 indicate that the correlations between all the liquidity measures and all the algorithmic trading proxies are significant. Effective half spread is significantly and positively correlated with the algorithmic trading proxy ($r(17391) = 0.319$ and $p < 0.01$). Share turnover exhibits a significantly negative correlation with the algorithmic trading proxy ($r(17391) = -0.323$ and $p < 0.01$). The magnitude of the correlation between algorithmic trading initiated by institutional investors and liquidity measures is lower than the one between algorithmic trading initiated by foreign investors and liquidity measures. The correlation between algorithmic trading initiated by institutional investors and effective half spread is positive ($r(17391) = 0.210$ and $p < 0.01$) whereas the correlation between algorithmic trading initiated by institutional investors and share turnover is negative ($r(17391) = -0.275$ and $p < 0.01$). Algorithmic trading which is originated from the foreign investors is positively correlated with effective half spread ($r(17391) = 0.240$ and $p < 0.01$) and is negatively correlated with share turnover ($r(17391) = -0.281$ and $p < 0.01$).

Correspondingly, the signs of the correlations of the control variables agree with the literature review. Realized volatility are positively related to effective half spread ($r(17391) = 0.530$ and $p < 0.01$) and share turnover ($r(17391) = 0.328$ and $p < 0.01$). The inverse of average price exhibits positive correlations with effective half spread ($r(17391) = 0.212$ and $p < 0.01$) and share turnover ($r(17391) = 0.048$ and $p < 0.01$). Furthermore, the market capitalization displays a negative correlation with effective half spread ($r(17391) = -0.204$ and $p < 0.01$). As firm size becomes larger, there is more liquidity, thus decreasing effective half spread. The correlation coefficient between the natural logarithm of market capitalization and the share turnover is -0.125 with the significance level of more than 99.9%, showing that when the firm size is bigger, there are more stocks available; thus, share turnover is lower. In addition, there is a strongly negative correlation between the algorithmic trading proxy and the logarithmic of market capitalization.

Table 4.5 Correlation Matrix for Daily Variables. *, ** and *** Denote Significance at the 10%, 5% and 1% Level

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Effective half spread	1							
2. Share turnover	-0.104***	1						
3. Algorithmic trading (all)	0.319***	-0.323***	1					
4. Algorithmic trading initiated by institutional investors	0.210***	-0.275***	0.832***	1				
5. Algorithmic trading initiated by foreign investors	0.240***	-0.281***	0.817***	0.637***	1			
6. Volatility	0.530***	0.328***	0.118***	0.078***	0.114***	1		
7. Inverse of average price	0.212***	0.048***	0.311***	0.231***	0.199***	0.163***	1	
8. Natural logarithm of market capitalization	-0.204***	-0.125***	-0.683***	-0.623***	-0.609***	-0.283***	-0.328***	1

2) Monthly Variable

Table 4.6 illustrates the Pearson's correlation matrix for the monthly variables. I found that the Amihud's illiquidity estimate is positively correlated with algorithmic trading (r(963) = 0.319 and $p < 0.01$) whereas liquidity ratio is negatively correlated with algorithmic trading (r(963) = -0.876 and $p < 0.01$). There are positive correlations between the Amihud's illiquidity estimate and the algorithmic trading initiated by institutional investors proxy, $r = 0.554$, $p < 0.01$; and between the Amihud's illiquidity estimate and the algorithmic trading initiated by foreign investors proxy, $r = 0.490$, $p < 0.01$. There are negative correlations between the liquidity ratio and the algorithmic trading initiated by institutional investors proxy, $r = -0.890$, $p < 0.01$ and between the liquidity ratio and the algorithmic trading initiated by foreign investors proxy, $r = -0.915$, $p < 0.01$. Lastly, there is no correlation between share turnover and monthly liquidity measures; therefore, I deducted this variable from the model.

Table 4.6 Correlation Matrix for Monthly Variables. *, ** and *** Denote Significance at the 10%, 5% and 1% Level

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Amihud's illiquidity estimate	1								
2. Liquidity ratio	-0.270***	1							
3. Algorithmic trading (all)	0.319***	-0.876***	1						
4. Algorithmic trading initiated by institutional investors	0.554***	-0.890***	0.949***	1					
5. Algorithmic trading initiated by foreign investors	0.490***	-0.915***	0.926***	0.914***	1				
6. Volatility	0.023	-0.174***	-0.010	0.273***	0.255***	1			
7. Inverse of average price	0.053*	-0.219***	0.332***	0.308***	0.237**	0.019	1		
8. Logarithmic of market capitalization	-0.392***	0.764***	-0.764***	-0.795***	-0.774***	-0.187***	-0.351***	1	
9. Share turnover	-0.006	-0.012	0.021	-0.096	-0.200**	0.033	0.040	-0.056*	1

4.4.1.2 Volatile Period

1) Daily Variable

Table 4.7 reports the correlation matrix for the daily variables during the volatile period. Effective half spread is positively correlated with algorithmic trading (r(1700) = 0.291 and $p < 0.01$) while share turnover is negatively correlated with algorithmic trading (r(1700) = 0.291 and $p < 0.01$). The magnitude of the correlation between effective half spread and algorithmic trading is lower during the volatile period than during the entire period. On the contrary, the magnitude of the correlation between share turnover and algorithmic trading is higher during the volatile period than during the entire period.

There are positive correlations between the effective half spread and the algorithmic trading initiated by institutional investors proxy, $r = 0.213$, $p < 0.01$; and between the effective half spread and the algorithmic trading initiated by foreign investors proxy, $r = 0.168$, $p < 0.01$. There are negative correlations between the share turnover and the algorithmic trading initiated by institutional investors proxy, $r = -0.329$, $p < 0.01$ and between the share turnover and the algorithmic trading initiated by foreign investors proxy, $r = -0.284$, $p < 0.01$.

Table 4.7 Correlation Matrix for Daily Variables during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Effective half spread	1							
2. Share turnover	-0.092***	1						
3. Algorithmic trading (all)	0.291***	-0.393***	1					
4. Algorithmic trading initiated by institutional investors	0.213***	-0.329***	0.866***	1				
5. Algorithmic trading initiated by foreign investors	0.168***	-0.284***	0.800***	0.657***	1			
6. Volatility	0.371***	0.366***	0.042*	0.038	0.046*	1		
7. Inverse of average price	0.214***	0.070***	0.314***	0.248***	0.187***	0.126***	1	
8. Natural logarithm of market capitalization	-0.140***	-0.101***	-0.670***	-0.646***	-0.628***	-0.214***	-0.332***	1

2) Monthly Variable

Table 4.8 reports the correlation matrix for the monthly variables during the volatile period. Amihud's illiquidity estimate is positively correlated with algorithmic trading ($r(94) = 0.542$ and $p < 0.01$) while liquidity ratio is negatively correlated with algorithmic trading ($r(94) = -0.910$ and $p < 0.01$). The magnitude of the correlation between Amihud's illiquidity estimate and algorithmic trading and between liquidity ratio and algorithmic trading is higher during the volatile period than during the entire period.

There are positive correlations between the Amihud's illiquidity estimate and the algorithmic trading initiated by institutional investors proxy, $r = 0.554$, $p < 0.01$; and between the Amihud's illiquidity estimate and the algorithmic trading initiated by foreign investors proxy, $r = 0.490$, $p < 0.01$. There are negative correlations between the liquidity ratio and the algorithmic trading initiated by institutional investors proxy, $r = -0.890$, $p < 0.01$ and between the liquidity ratio and the algorithmic trading initiated by foreign investors proxy, $r = -0.915$, $p < 0.01$.

Table 4.8 Correlation Matrix for Monthly Variables during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Amihud's illiquidity estimate	1								
2. Liquidity ratio	-0.437***	1							
3. Algorithmic trading (all)	0.542***	-0.910***	1						
4. Algorithmic trading initiated by institutional investors	0.554***	-0.890***	0.944***	1					
5. Algorithmic trading initiated by foreign investors	0.490***	-0.915***	0.926***	0.914***	1				
6. Volatility	0.358***	-0.337***	0.226**	0.273***	0.255**	1			
7. Inverse of average price	0.105	-0.239**	0.328***	0.308***	0.237**	0.198*	1		
8. Logarithmic of market capitalization	-0.642***	0.789***	-0.789***	-0.795***	-0.774***	-0.526***	-0.375***	1	
9. Share turnover	-0.121	0.081	-0.071	-0.096	-0.200*	0.151	0.080	0.002	1

4.4.2 The Effect of Algorithmic Trading on Liquidity

To test the null hypothesis whether the algorithmic trading has a relationship with liquidity or not, I estimated the following multivariable regression using various estimation techniques.

$$ESPREAD_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + \varepsilon_{it}$$

$$TURNOVER_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \varepsilon_{it}$$

For the monthly variables, in the previous section, I found that there is no correlation between share turnover and liquidity measures i.e. the Amihud's illiquidity estimate and the liquidity ratio. Therefore, I rewrote Equation 4.10 and 4.11 as:

$$LR_{im} = \alpha + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \varepsilon_{im} \quad (4.41)$$

$$ILLIQ_{im} = \alpha + \beta_1 AT_{im} + \beta_2 VOLATILITY_{im} + \beta_3 \left(\frac{1}{PRICE}\right)_{im} + \beta_4 LN(MARKET\ CAP)_{im} + \varepsilon_{im} \quad (4.42)$$

Initially, the independent variables need to be tested whether there is multicollinearity. The variance inflation factor outcomes for the daily and the monthly variables show that there is no multicollinearity (See Appendix B-2).

Assuming no heterogeneity, the pooled ordinary least square linear regression is carried out to investigate the effect of algorithmic trading on liquidity. Table 4.9 lists the regression coefficients of the independent variables (the algorithmic trading proxy, the share turnover, realized volatility, the inverse of the average price and the natural logarithm of market capitalization) on dependent variables (the effective half spread, the share turnover, the Amihud's illiquidity estimate and the liquidity ratio). Simple linear regression shows that there are significant relationships between the algorithmic trading proxy and the daily liquidity measures i.e. effective half spread and share turnover.

First, the coefficient of algorithmic trading on effective half spread is 0.0011 with the confidence level of more than 99.9%. When algorithmic trading changes by one standard deviation, which is 28.7851, effective half spread is changed by 28.7851 x 0.0011 = 0.0317%. As the average effective half spread is 0.2759, 0.0317% change in effective half spread is equivalent to 11.4765% change in effective half spread from its mean value. Therefore, an increase in algorithmic trading activity is related to wider effective half spread. The adjusted R-square is 0.4056 or 40.56% of the variation on the effective half spread can be explained by this model.

Second, the coefficient of algorithmic trading on share turnover is -1.4718×10^{-4} ($p < 0.01$). This implies that algorithmic trading has a negative relationship with share turnover. One standard deviation change in algorithmic trading leads to -0.0042 change in share turnover or -96.2862% from its average value. This is in accordance with the earlier research by Hendershott et al (2011) which showed that algorithmic trading and share turnover have negative relationships. The adjusted R-square is 0.39 or 39% of the variation on share turnover can be explained by this model.

Third, there is a strong statistical relationship between the liquidity ratio and the algorithmic trading proxy. It is found that lower liquidity ratio is associated with higher algorithmic trading proxy ($\widehat{\beta_1} = -9.3662\ and\ p < 0.01$). One standard deviation expansion in algorithmic trading leads to 305.3456 decrease in liquidity ratio, which is equivalent to 108.9 percent decline from the average value of liquidity ratio. The r-square is quite high, which is 81.84 percent, indicating that the model explains 81.84 percent of the variability of the response data around its mean. Finally, the algorithmic trading proxy has an insignificant regression weight with the Amihud's illiquidity estimate.

Table 4.9 Pooled OLS Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)	Model 3 Liquidity Ratio (t-statistics)	Model 4 Amihud's illiquidity (t-statistics)
Intercept	-0.1200***	0.0359***	-913.6321***	0.2298***
	(-7.693)	(55.002)	(-8.371)	(9.737)
Algorithmic trading	0.0011***	-1.4718x10^{-4***}	-9.3662***	5.3456x10^{-5}
	(25.478)	(-90.369)	(-35.114)	(0.927)
Volatility	0.5158***	0.0098***	-68.9867***	-0.0023
	(92.717)	(40.881)	(-10.415)	(-1.605)
The inverse of price	0.0871***	0.0025***	293.5146***	-0.0291***
	(14.959)	(9.644)	(7.019)	(-3.215)
Natural log of market cap	0.0168***	-0.0029***	62.8190***	-0.0141***
	(14.932)	(-63.577)	(7.988)	(-8.297)
Share turnover	-4.5978***			
	(-27.696)			
Adjusted R^2	40.56%	39.00%	81.84%	16.18%

One of the issues with using panel data is individual and time heterogeneity. Appendix B-3 shows that there are individual and time heterogeneity. The restricted F-test and the chi-square statistics are used to select the proper model and the results are shown in Appendix B-4 to B-5. As all the test statistics are significant, the fixed effects models are better choices. Therefore, I implemented the regression analysis using the two-ways fixed-effects for model 1, 2 and 4 as depicted in Table 4.10; whereas, for model 3, I conducted the regression analysis using the individual fixed-effects as shown in Table 4.11. Appendix B-6 demonstrates all regression coefficients estimated by other methods.

For the daily variables, all the coefficient estimates of the algorithmic trading proxy are significant. The regression results provide four important outcomes. First, algorithmic trading increases effective half spread ($\widehat{\beta_1}$ = 0.0011 and p < 0.01). Therefore, an increase in one unit of algorithmic trading proxy (1,000 baht of trading volume per traffic message) increases effective half spread by 0.0011% on average. One standard deviation increase in algorithmic trading which is equal to 28.7851 results in an increase in effective half spread by 0.0011 x 28.7851 = 0.0317%. As the average of effective half spread is 0.2759, this is equivalent to 11.49% increase from its mean value. This result is similar to the results yielded by Hendershott and Moulton (2011), van Ness et al. (2015) and Cartea et al. (2019), but is different from the result obtained by Hendershott et al. (2011) which is algorithmic trading narrows bid-ask spread.

Second, algorithmic trading decreases share turnover. For every additional unit change in the algorithmic trading proxy (1,000 baht of trading volume per traffic message), share turnover, on average, changes by -0.000158 unit. One standard deviation increase in algorithmic trading decreases share turnover by -0.000158 x 28.7851 = 0.00455 unit or 103% from the mean value of the share turnover. The magnitude of the effect of algorithmic trading on share turnover is significant. Moreover, the direction of the estimated share turnover coefficient is in line with the result found by Hendershott et al. (2011).

Table 4.10 Fixed-effect (Two-way) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	**Model 1 Effective Half Spread (t-statistics)**	**Model 2 Share Turnover (t-statistics)**	**Model 4 Amihud's illiquidity (t-statistics)**
Algorithmic trading	0.0011^{***} (23.659)	$-1.5808\text{x}10^{-4***}$ (-88.642)	$2.2068\text{x}10^{-4***}$ (3.249)

Table 4.10 (Continued)

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)	Model 4 Amihud's illiquidity (t-statistics)
Volatility	0.4681***	0.0078***	3.3650x10^{-5}
	(75.147)	(28.422)	(0.029)
The inverse of	0.0607	-0.0134***	0.1992***
price	(1.512)	(-7.466)	(4.344)
Natural log of			-0.0004
market cap			(-0.052)
Share turnover	-3.5726***		
	(-21.167)		
Adjusted R^2	26.55%	36.85%	-0.09%

Third, for the monthly variables, algorithmic trading enhances Amihud's illiquidity estimate, $\widehat{\beta_1}$ = 2.2068x10^{-4}, t(853) = 3.249 and $p < 0.01$. Therefore, when the algorithmic trading proxy increases by one standard deviation, which is 32.6008, Amihud's illiquidity estimate, on average, increases by 2.2068x10^{-4} x 32.6008 = 0.0072. Subsequently, as the mean value of the Amihud's illiquidity estimate is 0.0192, the Amihud's illiquidity estimate increases by 37.5 percent.

Finally, the individual-effect fixed-effect model indicates that algorithmic trading is significantly associated with negative liquidity ratio, $\widehat{\beta_1}$ = -8.1847, t(853) = -22.7535 and $p < 0.01$. Therefore, when the algorithmic trading proxy increases by one standard deviation, liquidity ratio, on average, decreases by -8.1847x32.6008 = 266.828 where 32.6008 is the standard deviation of the algorithmic trading proxy. Subsequently, the liquidity ratio is decreased by 95.13 percent, indicating that in the longer run, algorithmic trading deters liquidity.

Table 4.11 Fixed-effect (Individual) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)	Model 3 Liquidity Ratio (t-statistics)	Model 4 Amihud's illiquidity (t-statistics)
Algorithmic trading	0.0012*** (23.682)	-1.4718×10^{-4}*** (-90.369)	-8.1847*** (-22.754)	2.7440×10^{-4}*** (4.153)
Volatility	0.3704*** (64.139)	0.0099*** (37.441)	-59.5203*** (-10.246)	0.0014 (1.276)
The inverse of price	-0.1180*** (-2.846)	0.0025*** (9.631)	509.7520** (2.045)	0.2248*** (4.910)
Natural log of market cap		-0.0029*** (-61.703)	1.5815 (0.042)	-0.0007 (-0.098)
Share turnover	-3.6977*** (-21.011)			
Adjusted R^2	22.47%	35.95%	31.72%	-0.06%

4.4.3 The Causal Relationship between Algorithmic Trading Proxy on Liquidity

I analyzed the relationship between the algorithmic trading proxy and the liquidity measures using the two-stage least square estimation technique. This method ensures the causal relationship and solves for the endogeneity effect. The result of the two-stage least squares estimation is presented in Table 4.12. In the first stage regression, I estimated the algorithmic trading proxy as a function of an instrumental variable (IV). The result indicates that there is a positive and significant relationship between the algorithmic trading proxy and the instrumental variable after controlling for other variables (p < 0.01). Moreover, I calculated the correlation between the instrumental variable and liquidity to check for endogeneity and Table 4.13 reported the correlations. The results show that there is no correlation between the instrumental variable and effective half spread ($r(17391) = -0.0083$ and $p = 0.2713$), confirming the validity of the instrumental variable. However, the instrumental variable is correlated with the share turnover ($r(17391) = -0.0083$ and $p = 0.2713$). Therefore, the 2SLS analysis may not be a good estimation technique for share turnover as an increase in algorithmic trading may alter the level of share turnover.

Table 4.12 2SLS Analysis for the Impact of Algorithmic Trading Proxy on Liquidity Measures. *, ** and *** Denote Significance at the 10%, 5% and 1%.

Variable	**First Stage Algorithmic Trading**	**Second Stage Effective Half Spread**	**Second Stage Share Turnover**
Intercept	214.0539***	-0.4929**	0.0794***
	(90.665)	(-2.182)	(5.316)
Instrumental Variable	1.3736***		
	(4.036)		
Algorithmic trading		0.0032***	-3.3222×10^{-4}***
		(3.020)	(-4.777)
Volatility	-7.3319***	0.8472***	0.0115***
	(-4.980)	(83.925)	(17.203)
The inverse of price	21.6274***	-0.0398*	0.0055***
	(17.641)	(-1.701)	(3.530)
Natural log of market cap	-17.7628***	0.0453**	-0.0064***
	(-113.133)	(2.424)	(-5.211)
Adjusted R-squared	47.64%	52.64%	-3.59%

Table 4.13 Pearson's Correlation Analysis. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

	Effective Half Spread	**Share Turnover**
Instrumental Variable	-0.0083	-0.0459***
	(-1.100)	(-6.108)

From Table 4.12, the second-stage regressions affirm that there exist a significantly positive relationship between algorithmic trading and effective half spread ($\widehat{\beta_1}$ = 0.0032 and p < 0.01) and a significantly negative relationship between algorithmic trading and share turnover ($\widehat{\beta_1}$ = -0.0003 and p < 0.01). The directions of the effect of algorithmic on liquidity measures are consistent with the results obtained from the correlation analysis, the pooled OLS regression and the fixed-effects models. The extents in which algorithmic trading affects liquidity measures estimated by the two-stage least square regression are larger than the ones estimated by other methods.

When algorithmic trading augments by one standard deviation, the effective half spread is increased by 0.0032 x 28.7851 = 0.0921 percent on average. This is associated with a 33.38% increase in effective half spread from its associated mean value. On the contrary, share turnover is contracted by 0.00033 for every additional unit change in the algorithmic trading proxy. This implies that one standard deviation change in the algorithmic trading proxy reduces share turnover, on average, by 0.0095 unit or 215.89% from the mean share turnover. Thus, an increase in algorithmic trading deteriorates liquidity by widening effective half spread and diminishing share turnover.

4.4.4 The Effect of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxy on Liquidity

The proxies for algorithmic trading initiated by institutional and foreign investors are calculated. In this section, I investigated the role of algorithmic trading initiated by institutional and foreign investors on ameliorating or deteriorating liquidity. From the section 4.4.2, I found that the two-way fixed-effect model is the most appropriate model in estimating the relationship between algorithmic trading and liquidity measures. In the similar fashion, I employed this method to estimate the regression coefficients of the algorithmic trading initiated by each type of investors proxies.

From the two-way fixed-effects model, the algorithmic trading initiated by institutional and foreign investors proxies as well as the interaction between these two proxies exhibit significant relationships as displayed in Table 4.14. The OLS regression possesses the same effect as the fixed-effect regression (See appendix B-7). Algorithmic trading initiated by institutional investors proxy, algorithmic trading initiated by foreign investors proxy and the interaction term between these two proxies increase effective half spread ($\widehat{\beta_1}$ = 2.7425x 10^{-4}, $\widehat{\beta_2}$ = 7.7773x10^{-4} and $\widehat{\beta_3}$ = 2.7933x10^{-6} and p < 0.01). One standard deviation increase in algorithmic trading initiated by institutional investors is associated with 2.7425x10^{-4} x 81.5097 = 0.0224% increase in effective half spread. This is equivalent to 8.12% increase from the mean effective half spread. Correspondingly, effective half spread is also increased, on average, by 7.7773x10^{-4} x 38.7142 = 0.0301% or 10.91% from the mean value due to one standard deviation increase in algorithmic trading initiated by foreign investors. Obviously, the effect of algorithmic trading initiated by foreign investors on effective half spread is more profound than the effect of algorithmic trading initiated by institutional investors. In addition, the interaction between algorithmic trading initiated by institutional and foreign investors further widens effective half spread by 0.0088% or 3.19% from the mean value.

On the other hand, algorithmic trading initiated by institutional investors proxy, algorithmic trading initiated by foreign investors proxy and the interaction term between these two proxies shrink share turnover ($\widehat{\beta_1}$ = -2.8491x10^{-5}, $\widehat{\beta_2}$ = -6.8955x10^{-5} and $\widehat{\beta_3}$ = -6.6613x10^{-8} and p < 0.01). An increase in one standard deviation of algorithmic initiated by institutional and foreign investors decreases share turnover by 0.0023 and 0.0027 respectively which are equal to 52.27% and 61.36% from the mean share turnover respectively. Consistently, the interaction between two types of algorithmic trading proxies leads to a lower share turnover by 0.0022 unit or 4.78% from its mean value.

Table 4.14 Fixed-effects Two-Way Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables on Liquidity Measures. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	**Model 1 Effective Half Spread (t-statistics)**	**Model 2 Share Turnover (t-statistics)**	**Model 3 Liquidity Ratio (t-statistics)**	**Model 4 Amihud's illiquidity (t-statistics)**
AT initiated by institutional investors	2.7425×10^{-4}*** (16.124)	-2.8491×10^{-5}*** (-37.082)	-0.2398 (-1.508)	1.0859×10^{-4}*** (3.897)
AT initiated by foreign investors	7.7773×10^{-4}*** (18.785)	-6.8955×10^{-5}*** (-36.854)	0.2409 (0.522)	1.4219×10^{-4}* (1.758)
AT initiated by institutional x foreign investors	2.7933×10^{-6}*** (14.131)	-6.6613×10^{-8}*** (-7.188)	0.0142*** (8.367)	8.9419×10^{-7}*** (3.006)
Volatility	0.4663*** (73.648)	0.0087*** (30.160)	-32.1850*** (-4.912)	-9.4136×10^{-5} (-0.082)
The inverse of price	0.0671 (1.633)	-0.0227*** (-11.806)	-436.9838* (-1.657)	0.1899*** (4.111)
Natural log of market cap			-19.8853 (-0.505)	-3.7609×10^{-4} (-0.055)
Share turnover	-4.3205*** (-26.524)			
Adjusted R^2	25.83%	31.72%	19.17%	-0.08%

The result shows that AT initiated by foreign investors has more profound effect on undermining liquidity in term of daily effective half spread and daily share turnover whereas AT initiated by institutional investors plays a larger role in distorting liquidity in term of Amihud's illiquidity estimate in the long run. The interaction between algorithmic trading initiated by each type of investors also augments the effect.

For the monthly liquidity measures, I found that the Amihud's illiquidity estimate is increased by 1.0859×10^{-4} x 88.2576 = 0.0096 or 49.92 percent from the mean due to one standard deviation increase in algorithmic trading initiated by institutional investors. Furthermore, an increase in algorithmic trading initiated by foreign investors by one standard deviation increases the Amihud's illiquidity estimate by 0.0055 or 30.12 percent from the mean value. The same effect is also valid for the interaction term. An increase in one standard deviation of the interaction term increases the Amihud's illiquidity estimate by 0.0031 or 16.02 percent from the mean value.

4.4.5 The Effect of Algorithmic Trading on Liquidity during the Volatile Period

I derived an empirical testing to examine the effect of algorithmic trading on liquidity when the market becomes highly volatile. Table 4.15 illustrates the regression coefficients when employed the pooled OLS method. From the table, there is a positive relationship between the algorithmic trading proxy and effective half spread, indicating that liquidity is worsened when algorithmic trading increases. The regression results of the Model 2 and 3 reveal that when algorithmic trading increases, share turnover and liquidity ratio will be decreased, inferring distorted liquidity. Lastly, there is no significant relationship between algorithmic trading and Amihud's illiquidity estimate. These relationships during the volatile period are consistent with the relationships during the overall periods.

As pooled OLS estimation method assumes that there are no multicollinearity and heterogeneity, I tested for the presence of these issues. Therefore, I examined all models for the presence of multicollinearity using the variance inflation factor (See appendix B-8). I found that there is no multicollinearity in both daily and monthly models. Therefore, all of the independent variables can be included in the models. For the presence of heterogeneity, I examined the daily liquidity models by plotting the mean value of the dependent variables across individual and time. From the plots, there are heterogeneity across both individuals and time effects (See appendix B-9). The restricted F-test shows that the fixed-effect model is an appropriate estimation tool (See appendix B-10).

Therefore, the two-way fixed-effects models are estimated for the daily variables. The results are depicted in Table 4.16. Consistent with the pooled OLS technique, the two-way fixed-effects model points out that algorithmic trading widens the effective half spread while diminishes share turnover.

Table 4.15 Pooled OLS Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)	Model 3 Liquidity Ratio (t-statistics)	Model 4 Amihud's illiquidity (t-statistics)
Intercept	-0.1151**	0.0387***	-719.2748	0.1718***
	(-2.175)	(20.031)	(-1.645)	(3.932)
Algorithmic trading	0.0014***	-1.6392×10^{-4}***	-10.1328***	8.8158×10^{-5}
	(8.811)	(-33.604)	(-11.860)	(1.033)
Volatility	0.2210***	0.0068***	-47.8539**	0.0015
	(18.544)	(14.913)	(-2.156)	(0.665)
The inverse of price	0.1177***	0.0045***	289.794**	-0.0248*
	(5.982)	(5.719)	(2.254)	(-1.930)
Natural log of market cap	0.0235***	-0.0031***	44.262	-0.0106***
	(6.062)	(-22.301)	(1.469)	(-3.513)
Share turnover	-2.2654***			
	(-3.813)			
Adjusted R^2	25.94%	47.62%	85.00%	41.62%

Table 4.16 Two-way Within-Group Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)
Algorithmic trading	0.0012***	-1.3854x10^{-4}***
	(7.705)	(-24.787)
Volatility	0.1990***	0.0037***
	(15.331)	(6.823)
The inverse of price	-0.0675	0.0079
	(-0.2214)	(0.607)
Share turnover	-1.0146*	
	(-1.751)	
Adjusted R^2	10.93%	25.25%

Our test results suggest that there is a positive relationship between algorithmic trading and effective half spread. When algorithmic trading increases by one standard deviation, effective half spread widens by 0.0348 percent on average which increases from its mean value by 13.02 percent. Furthermore, share turnover exhibits a negative relationship with algorithmic trading. In particular, the share turnover decreases by 0.0040 on average per each standard deviation increase in algorithmic trading. This means that share turnover is changed by 83.74 percent from its average value, which is quite significant. For the monthly liquidity models, the ordinary least square method is used to estimate the slope coefficient as the data is the cross-sectional data. From Table 4.15, the coefficient of the algorithmic trading proxy on the liquidity ratio is -10.1328 with t-value of -11.860. This predicts that for every additional increment of algorithmic trading proxy by one standard deviation, the liquidity ratio will be decreased by 344.0859 or 122.21 percent from the average value of the liquidity ratio. The last column presents the coefficient of algorithmic trading on the Amihud’s (2002) illiquidity estimate which affirms that there is no significant relationship.

Overall, the results show that during the volatile market, algorithmic trading increases effective half spread, lowers share turnover, reduces liquidity ratio and exerts no impact on Amihud's illiquidity estimate. The magnitude of the effect of algorithmic trading on effective half spread and liquidity ratio is higher during the volatile period than during the overall periods whereas the magnitude of the effect of algorithmic trading on share turnover during the volatile period is lower than the one during the overall periods.

4.4.6 The Effect of Algorithmic Trading Initiated by Institutional and Foreign Investors on Liquidity during the Volatile Period

To delve further, I examined the role of algorithmic trading initiated by institutional and foreign investors on liquidity during the volatile period. Table 4.17 reports the regression coefficients, estimated by the pooled OLS estimation technique. The dataset used for Model 1 and 2 is a panel data; therefore, it might be subjected to heterogeneity. There is two-way heterogeneity for a panel data as shown in previous section. Therefore, the two-way fixed-effect models are used to estimate the relationship between algorithmic trading and liquidity for Model 1 and 2 as shown in Table 4.18. As Model 3 and 4 are the monthly liquidity model, the dataset is the cross-sectional data. Therefore, the ordinary least square estimation method can be used. The regression analyses yield the following results.

Table 4.17 Pooled OLS Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables on Liquidity Measures during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)	Model 3 Liquidity Ratio (t-statistics)	Model 4 Amihud's illiquidity (t-statistics)
Intercept	0.0283 (0.481)	0.0442*** (20.043)	-1046.56*** (-3.303)	0.1575*** (4.033)
AT initiated by institutional investors	2.3397×10^{-4}*** (3.304)	-4.6153×10^{-5}*** (-16.868)	-0.0528 (-0.134)	1.9456×10^{-4}*** (3.993)
AT initiated by foreign investors	2.3550×10^{-4} (1.472)	-7.9522×10^{-5}*** (-12.436)	1.1750 (1.014)	3.5096×10^{-4}** (2.456)
AT initiated by institutional x foreign investors	7.9518×10^{-7} (0.992)	-1.7281×10^{-7}*** (-5.202)	0.0276*** (8.961)	1.9662×10^{-6}*** (5.173)
Volatility	0.2282*** (18.791)	0.0066*** (13.631)	-15.6762 (-1.016)	0.0020 (1.039)
The inverse of price	0.1466*** (7.398)	0.0016* (1.885)	131.7357 (1.429)	-0.0257** (-2.263)
Natural log of market cap	0.0116*** (2.717)	-0.0034*** (-21.601)	83.6122*** (3.782)	-0.0085*** (-3.119)
Share turnover	-4.12894*** (-7.096)			
Adjusted R^2	23.43%	43.05%	92.49%	55.51%

Table 4.18 Two-way Within-group Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables on Liquidity Measures during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Variable	**Model 1 Effective Half Spread (t-statistics)**	**Model 2 Share Turnover (t-statistics)**
AT initiated by institutional investors	$3.1541 \times 10^{-4***}$	$-2.2101 \times 10^{-5***}$
	(5.640)	(-8.755)
AT initiated by foreign investors	$8.9652 \times 10^{-4***}$	$-5.6847 \times 10^{-5***}$
	(7.052)	(-9.973)
AT initiated by institutional x foreign investors	$2.8748 \times 10^{-6***}$	$-6.2205 \times 10^{-8**}$
	(4.542)	(-2.129)
Volatility	0.2045^{***}	0.0038^{***}
	(15.747)	(6.355)
The inverse of price	-0.0725	0.0065
	(-0.236)	(0.461)
Share turnover	-1.5922^{***}	
	(-2.933)	
Adjusted R^2	11.32%	15.31%

First, there are positive relationships between all the algorithmic trading initiated by institutional and foreign investors proxies as well as their interaction term and effective half spread. In particular, an increase in one standard deviation of the algorithmic trading initiated by institutional and foreign investors proxies increases effective half spread by $3.1541 \times 10^{-4} \times 81.8384 = 0.0258$ percent and $8.9652 \times 10^{-4} \times 36.4103 = 0.0326$ percent respectively. They contribute to 9.65 percent and 12.19 percent increase in effective half spread from its mean value respectively. Furthermore, the interaction between two types of algorithmic trading proxies also leads to an increase in effective half spread by 0.0085 percent which represents 3.20 percent of its mean value.

Second, the slope coefficients of the algorithmic trading initiated by institutional and foreign investors proxies and their interaction term on share turnover are -2.2101×10^{-5}, -5.6847×10^{-5} and -6.2205×10^{-8} respectively. Hence, share turnover decreases by 0.0018, 0.0021 and 0.0002 respectively, which are equivalent to 37.68, 43.12 and 3.86 percent decline from the average share turnover.

Inconsistent with the previous result, the interaction between algorithmic trading initiated by institutional and foreign investors increases liquidity ratio by 94.9576 or 33.73 percent from the mean value. Moreover, the algorithmic trading initiated by institutional and foreign investors and their interaction term exhibit significant positive relationships with Amihud's illiquidity estimate. Specifically, an increase in algorithmic trading initiated by institutional and foreign investors escalates the Amihud's illiquidity estimate by 0.0172 and 0.0137 which are equal to 93.32 and 74.35 percent from its average value respectively. Consistently, the interaction term also raises the Amihud's illiquidity estimate by 0.0068 which is equal to 36.76 percent from the average value. Overall, the effect of AT initiated by foreign investors on reducing liquidity is more profound than the effect of AT initiated by institutional investors for short run. On the contrary, for the long run, the effect of AT initiated by institutional investors on reducing liquidity is more profound than the effect of AT initiated by foreign investors.

4.5 Conclusion

Algorithmic trading has gained importance in the stock market in an emerging market. Yet, the empirical study on this topic is still few. This chapter investigates the impact of algorithmic trading on liquidity in the Stock Exchange of Thailand. This study of this topic is useful for the regulators to ensure liquid market. I used the dataset of SET100 stocks from March 2016 to December 2016. Due to the nature of panel data, I exploited various estimation techniques in order to assure accurate results by employing the variance inflation factor test, various panel data estimation techniques and the 2SLS analysis.

All in all, the results reveal that an increase in algorithmic trading in the Stock Exchange of Thailand widens effective half spread by 11.49 percent from its mean, lessens share turnover by 103 percent from its mean and lowers liquidity ratio by 37.50 percent from its mean. There is no evidence that algorithmic trading is associated with Amihud's illiquidity estimate. Therefore, algorithmic trading deteriorates liquidity, which contradicts to the result by Hendershott et al., but concurs with the results by Hendershott and Moulton (2011), van Ness et al. (2015), Upson and van Ness (2017), Cartea et al. (2019) and Manahov (2016).

To establish a causal relationship, the 2SLS regression is analyzed. The presence of the behavior of algorithmic traders exhibited in the market is used as an instrumental variable. The 2SLS results reinforced that algorithmic trading causes effective half spread to increase and share turnover to decrease. One standard deviation increase in algorithmic trading increases effective half spread by 33.38 percent and share turnover by 215.89 from their mean values.

There are two hypotheses to explain these results. The first hypothesis is that when information quality is high, the informed investors will submit and cancel limit orders in the limit order. The order submissions and cancellations elevate volatility. Therefore, when volatility is high, liquidity providers withdraw from the market (Goettler, Parlour, & Rajan, 2009). This hypothesis is called the informed limit order book hypothesis. An increase in message traffic signals information asymmetry and leads to lower liquidity. Another hypothesis is the AT adverse selection risk hypothesis. An increase in algorithmic trading increases adverse selection risks, lowering liquidity.

Additionally, as share turnover represents the level of information asymmetry, a decline in share turnover may represent increasing information asymmetry in the market. As the result indicates that algorithmic trading is associated with lower share turnover, an increase in algorithmic trading is therefore, related to an increase in information asymmetry.

Many researches show that informed investors possess private information and therefore, impose adverse selection risks onto other traders (Chaboud et al., 2014). As bid-ask spread incorporates adverse selection into it, a wider bid-ask spread may be due to an enlarge in adverse selection component in the bid-ask spread. High latency traders are reluctant to participate and thus require higher compensation in term of bid-ask spread when trading with better-informed traders. In this case, better-informed traders are algorithmic traders. Furthermore, as liquidity ratio is related to depth, the reverse relationship between algorithmic trading and liquidity ratio contends that algorithmic trading reduces order depth. Therefore, there are less orders available at certain price levels inferring declining participation rate. In addition, this result is corresponded with the result from the previous section, which indicates that algorithmic traders are informed traders.

Furthermore, the analysis of algorithmic trading initiated by institutional and foreign investors are conducted to study the effect associated with each type of investors. Algorithmic trading initiated by institutional and foreign investors and their interaction term all deteriorate liquidity. One standard deviation increase in algorithmic trading initiated by institutional investors increases effective half spread by 8.12 percent from its mean, decreases share turnover by 52.27 percent from its mean and increases Amihud's illiquidity estimate by 49.92 percent from its mean. One standard deviation increase in algorithmic trading initiated by foreign investors increases effective half spread by 10.91 percent from its mean, decreases share turnover by 61.36 percent from its mean and increases Amihud's illiquidity estimate by 30.12 percent from its mean. One standard deviation increase in the interaction term increases effective half spread by 3.19 percent from its mean, decreases share turnover by 4.78 percent from its mean and increases Amihud's illiquidity estimate by 16.02 percent from its mean.

Clearly, algorithmic trading initiated by foreign investors has more profound effects in decreasing liquidity in the short run in term of share turnover and effective half spread than algorithmic trading initiated by institutional investors has. Many researches (Kim & Yi (2015) and Seashole (2004)) showed that foreign investors possess information advantages and are better-informed investors, compared to other types of investors. Therefore, as foreign investors are better-informed, trading with algorithmic initiated by foreign investors exacerbates information asymmetry.

In the longer run, the interaction between algorithmic trading initiated by both investors increases liquidity ratio while algorithmic trading initiated by both types of investors and its interaction term augment the illiquidity estimate, inferring that even in the long run, liquidity is distorted due to algorithmic traders. In contrary, algorithmic trading initiated by institutional investors has more effect in distorting liquidity in term of increasing Amihud’s illiquidity estimate than algorithmic trading initiated by foreign investors has.

In addition, I investigated the effect of algorithmic trading on liquidity during the volatile period. Similar results prevail during the volatile period and furthermore, the effect is larger during the volatile period than during the entire period. In particular, algorithmic traders increase effective half spread by 13.02 percent from the mean, which is more than during the entire period (11.49 percent from the mean). Algorithmic trading decreases share turnover by 83.74 percent from the mean during the volatile period which is less than during the entire period (103 percent from the mean). Therefore, algorithmic traders contribute in distorting liquidity during the volatile period, worsening the market quality. However, it should be noted that the effect of algorithmic trading on share turnover is lower during the volatile period than during the entire period. Therefore, it shows that algorithmic traders do not withdraw from the market but require larger spread during the volatile period. This also corresponds with the larger average value of the algorithmic trading proxy during the volatile period. During the volatile period, algorithmic trading initiated by foreign investors also plays more role in distorting liquidity in term of enlarged effective spread and share turnover.

All in all, all types of algorithmic trading proxy exhibit negative relationship with liquidity. The understanding on the role of algorithmic trading on liquidity is essential to ensure healthy market quality for all types of investors.

CHAPTER 5

THE IMPACT OF ALGORITHMIC TRADING ON PRICE EFFICIENCY

5.1 Introduction

The role of financial markets is to ensure that prices are efficient. Therefore, price efficiency is an essential concept for market quality. Price efficiency allows efficient capital allocation and risk management. This eventually contributes to economic growth. Price efficiency reflects the degree in which the asset prices incorporate all available information in term of both speed and accuracy (Chordia & Swaminathan, 2000). It also identifies the level of mispricing in the securities. To capture the market quality, one needs to understand price efficiency as well because liquidity measures do not capture the information component of the market quality. For example, narrow bid-ask spread without the participation of informed traders does not contain information. O' Hara (2003) argued that liquidity represents the transaction cost and price discovery represents the risk. Liquidity and price discovery are, therefore, associated with asset pricing. Traditional asset pricing models assume symmetric information.

However, information is diverse among agents. Furthermore, stock prices do evolve and respond to information. Price formation is the process in which new information incorporates into prices, or how "latent demands are translated into realized prices and volumes," (Madhavan, 2002). Grossman and Stiglitz (1980) theorized that the prices set by informed investors convey information to the noise or uninformed investors. Therefore, the cause of price inefficiency is market imperfection such as information asymmetry.

The increase in algorithmic trading activities raise questions about their impact on price efficiency. Algorithmic trading (AT) has many features which may affect price efficiency. First, algorithmic traders obtain and route orders in a very rapid manner. The reduction in latency enables algorithmic trades not only to respond rapidly to the fundamental information, but also to gather high-frequency information such as order books. Algorithmic traders monitor the market closely and detect when the stock prices deviate from the efficient prices and take the position to profit from their trades. They can also access the market easily and thus, can adjust their portfolio more promptly upon the arrival of new fundamental information. Therefore, algorithmic trading enhances price efficiency by increasing price discovery.

Second, their holding periods are very short and typically result in zero net position at the end of the trading day. Classical finance would suggest that as long as the traders are rational, the holding periods are independent of the prices. Hasbrouck (1988) found that the relationship between trades and quote revision convey information. However, Froot, Scharfstein, and Stein (1992) showed that a market with many short-horizon traders is less efficient because traders trade on the information which is not related to fundamentals.

Third, they utilize different venues and co-locations in order to reduce latency. This should help to facilitate price efficiency. Fourth, their orders are typically small-sized. Numerous researches establish a positive relationship between trade size and price discovery. Easley and O’ Hara (1987) and Glosten (1989) found that the larger the trade is, the bigger the information it contains. Hasbrouck (1988) also presented a strong evidence that the larger the volume the trade is, the more information it contains. Fifth, algorithmic trading impairs price efficiency by increasing the noise in the market as algorithmic traders are associated with higher adverse selection cost and extreme volatility.

Therefore, our research questions become:

RQ# 1: What is the effect of algorithmic trading on price efficiency?

RQ# 2: Is there a causal relationship between algorithmic trading and price efficiency?

RQ# 3: What are the effects of algorithmic trading initiated by each type of investors on price efficiency?

RQ# 4: What is the effect of algorithmic trading on price efficiency during the volatile period?

RQ# 4: What are the effect of algorithmic trading initiated by institutional and foreign investors on price efficiency during the volatile period?

These questions are important for the regulators to ensure that the algorithmic traders do not hinder the price efficiency process.

5.2 Literature Review

In a continuous-time and no-arbitrage market, price changes are due to return innovation. There are two dimensions regarding the price efficiency. One is the process in which market participants incorporate existing information into securities prices. Another is the process in which the market participants acquire new information about securities and then use that information to incorporate into prices. While traders incorporate existing information into prices, price efficiency may be diminishing due to reducing information acquisition (Fama, 1970). Admati and Pfleiderer (1988) stated that given informed investors with homogeneous information set, an increase in number of informed traders benefits liquidity traders. On the contrary, the informed investors with heterogenous information set increase adverse selection costs.

Several models are developed to explain the relationship between algorithmic traders and price discovery. Jovanovic and Menkveld (2016) modelled two characteristics of high frequency traders, which are 1) high frequency traders as market makers who provide liquidity and 2) high frequency traders who acquire and process information in a very rapid manner. They found that high frequency traders can avoid adverse selection costs, the major costs faced by traditional market makers, by increasing their participation during high information periods. By doing so, they impose adverse selections to other types of investors, which eventually lower trades.

Researchers found that algorithmic trading is associated with price informativeness. Biais et al. (2015) revealed that high frequency traders accelerate the incorporation of information into prices because of their superior signal processing abilities. Zhang (2018) provided the evidence that high frequency traders incorporate hard information into prices at higher speed and are more likely to trade. Therefore, they contribute to more efficient information. Hendershott and Moulton (2011) found that HFT is associated with a decrease in the noise component of the prices.

Empirical papers find that algorithmic trading contributes to enhanced price efficiency. Brogaard et al. (2014) confirmed the result previously modelled by Jovanovic and Menkveld (2016). High frequency traders gather public information and then, pass on adverse selection costs onto other market participants through their liquidity supplying high frequency trading. On the other hand, the liquidity demanding high frequency traders trade in the same direction as the efficient price and in different direction from the transitory pricing error. Hence, this increases price efficiency, but lessens market efficiency. Brogaard et al. (2014) showed that high frequency traders enhance price efficiency by trading in the same direction with information. Hendershott and Riordan (2009) utilized the data with an identification of the trades with fee rebates which are designated for algorithmic trading. They presented the evidence that algorithmic traders closely monitor the market-liquidity and short-run price predictivity. Therefore, as liquidity demanders, algorithmic traders can determine whether prices deviate from the fundamental values. And, in response, they adjust their orders according to the arrival of new information. This, as a result, moves the prices towards the efficient prices. Their trades resulted in a 20% increase in permanent price impact and a 40% increase in information. In the foreign exchange, algorithmic trading also improves price efficiency (Chaboud et al., 2014)

Besides increasing price efficiency, algorithmic trading is also linked to price discovery. Hendershott et al. (2011) implemented a vector autoregression to investigate the relationship between algorithmic trading and price discovery. They found that an increase in algorithmic trading increases quote informativeness because algorithmic traders monitor the order flow and price information closely and update their orders quickly. Therefore, their limit orders always reflect all the available data. As a result, their adverse selection cost is reduced as evident in Hendershott et al.' findings. Riordan and Storkenmaier (2012) investigated the effect of algorithmic trading on price discovery upon the reduction of system latency of the exchange. Using the Hasbrouck (1991a)'s cumulative impulse response function and the variance decomposition, they found that price discovery was improved from 43% to 90% which is the result of more informative quotes posted by the liquidity suppliers. Algorithmic traders search the market for price deviation and place the orders to gain profits. In the meantime, this helps to increase the market efficiency.

On the contrary, Zhang (2010) found a negative relationship between HFT and price discovery. Upon the arrival of fundamental news, stock prices are overshot when HFT activities are high. This is because HFT only focuses on the order flow, but not the real fundamental information. Along the same line, Weller (2017) presented the evidence that algorithmic trading reduces the price informativeness. Gider, Schnickler, and Westheide (2016) reported decreased market efficiency in association with high frequency trading using the method proposed by Bai, Philippon, and Savov (2016). They measure the amount in which the current stock prices predict future earnings. This affirms that HFT can only predict the order flows and thus, they do not have the motivation to seek fundamental information.

5.3 Sample and Methodology

5.3.1 Algorithmic Trading Measurement

I measured the algorithmic trading activities by implementing the method proposed by Hendershott et al. (2011). They proposed a normalized message traffic as a proxy for AT activities because AT is associated with increasing the number of orders submitted to the market while the ratio of order executed to the order submissions reduces. Therefore, the normalized message traffic or AT proxy can be computed by:

$$AT_{it} = -\frac{V_{it}}{MT_{it}} \tag{5.1}$$

where AT_{it} is the algorithmic trading proxies for stock i for day t, V_{it} is the trading volume for stock i for day t and MT_{it} is the message traffic, which include all order submissions and transaction for stock i for day t.

5.3.2 Price Efficiency Measurement

I used the standard deviation of the pricing error as the measurement of price efficiency. Hasbrouck (1993) introduced a method to measure the standard deviation of pricing error (See appendix C-1 for the derivation). The return and the signed trade variables can be constituted as the functions of the current and lagged innovative disturbances. Therefore, the vector moving average models become:

$$r_t = \sum_{i=0}^{10} a_i^* v_{1,t-i} + \sum_{i=0}^{10} b_i^* v_{2,t-i}, \tag{5.2}$$

$$x_t = \sum_{i=0}^{10} c_i^* v_{1,t-i} + \sum_{i=0}^{10} d_i^* v_{2,t-i}, \tag{5.3}$$

where r_t is the return $(p_t - p_{t-1})$ and for the purpose of this framework, x_t is the signed of the volume of trade variable. As the pricing error is defined as the function of information-correlated and information-uncorrelated terms, the pricing error variance is:

$$\sigma_s^2 = \alpha^2\sigma_s^2 + \sigma_\eta^2, \tag{5.4}$$

For the ease of computation, by imposing the Beveridge and Nelson (1981) restriction, I used the standard of pricing error as the measure of pricing efficiency. Hasbrouck (1993) established the lower bound for the variance of pricing error (σ_s^2) as:

$$VAR(Pricing\ Error) = \sigma_s^2 = \tag{5.5}$$
$$\sum_{j=0}^{\infty}[-\sum_{k=j+1}^{\infty} a_k^* \quad -\sum_{k=j+1}^{\infty} b_k^*]\, Cov(v) \begin{bmatrix} -\sum_{k=j+1}^{\infty} a_k^* \\ -\sum_{k=j+1}^{\infty} b_k^{*\prime} \end{bmatrix}.$$

5.3.3 Model Specification

5.3.3.1 Linear Regression Model

To analyze the relationship between algorithmic trading and price efficiency, a panel data analysis is performed by using the pooled ordinary least square. Thus, the model specification is:

$$SD(Pricing\ Error)_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \tag{5.6}$$
$$\beta_3\left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + \varepsilon_{it}$$

The description of dependent and independent variables is listed on Table 5.1.

Table 5.1 Description of the Variables

Variables	Description
Dependent	
SD(PRICING ERROR)	The standard deviation of pricing error which is the price efficiency measure
Independent	
AT	Algorithmic trading. The negative ratio of the volume traded to the traffic messages
VOLATILITY	Daily realized volatility with the sampling frequency of five minutes
PRICE	The daily average price traded
MARKET CAP	Market capitalization is the total market value of the company's outstanding shares
TURNOVER	Share turnover is the total number of shares traded by the average number of shares outstanding over a period

Following Hendershott et al. (2011), the control variables are volatility, the natural logarithmic of market capitalization, the inverse of price and share turnover. Control variables are the variables that might affect price efficiency. I included these variables in the model in order to isolate the effect of algorithmic trading on price efficiency. For volatility, I used the realized volatility whereas for the inverse of price, I used the inverse of average price. Daily realized volatility is computed by:

$$RV_{it} = \sqrt{\frac{\sum_{t=1}^{d}(R_{it} - \bar{R})^2}{d-1}}, \tag{5.7}$$

where RV_{it} is the realized volatility, $\bar{R}$ is the mean stock return and d is the number of periods during the measured time. Furthermore, the variance inflation factor (VIF) is computed to assure that there is no multicollinearity.

The multiple regression analysis is used to investigate whether there is no relationship between algorithmic trading and price efficiency. So, the null hypothesis becomes:

H_0: $\beta_1 = 0$

H_a: β_1 is not equal to 0.

The pooled OLS regression analysis assumes that there is no heterogeneity. As the panel data is subjected to heterogeneity, I applied two measures to examine this problem. First is the plot of the mean across individual effect and time effect. Second, I employed the restricted F-test to assess whether there is heterogeneity. To alleviate the heterogeneity, I implemented the fixed-effects and the random-effects models. Therefore, the fixed-effects model becomes:

$$SD(Pricing\ Error)_{it} = \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + \varepsilon_{it}, \quad (5.8)$$

where $SD(Pricing\ Error)_{it}$ is the mean-corrected value for the standard deviation of the pricing error for stock *i* on day *t* and AT_{it} is the mean-corrected value for the algorithmic trading proxy for stock I on day t. For control variables, $VOLATILITY_{it}$, $\left(\frac{1}{PRICE}\right)_{it}$, $LN(MARKET\ CAP)_{it}$ and $TURNOVER_{it}$ are the mean-corrected values for the realized volatility, the inverse of average price, the natural logarithm of market capitalization and the share turnover.

The random-effects model is specified as:

$$SD(Pricing\ Error)_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + w_{it} \quad (5.9)$$

where

$$w_{it} = \varepsilon_i + u_{it} \quad (5.10)$$

where w_{it} is the composite error.

As a result, the fixed-effects and the random-effects for the individual-effect, the time-effect and the twoways-effect are conducted. The restricted F-test and the Hausman test are used to determine the appropriate estimation techniques.

Literature review conveys that mostly, algorithmic trading is associated with higher price efficiency. Therefore, I hypothesized that algorithmic trading has a positive effect on price efficiency.

5.3.3.2 Two-stage Least Squares Estimation

Various researchers found that algorithmic trading causes an improvement in price efficiency; while Han, Tang, and Yang (2016) suggested that information attracts more traders. Therefore, algorithmic trading and price efficiency may be endogenous variables. To establish the causal relationship between algorithmic trading and price efficiency and to eliminate the effect of endogeneity, the two-stage least squares regression is estimated. As the previous section, the occurrence of the market behavior of the algorithmic trading is used as an instrumental variable. Therefore, the instrumental variable is equal to 1 after October 2016 and 0 otherwise.

The first stage regression can be expressed as:

$$\widehat{AT}_{it} = \alpha + \beta_1 IV_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \mu_{it}. \quad (5.11)$$

In the second stage, the effect of algorithmic trading on price efficiency model can be estimated using the following equation:

$$SD(Pricing\ Error)_{it} = \alpha + \beta_1 \widehat{AT}_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \mu_{it} \quad (5.12)$$

5.3.3.3 The Volatile Market

To understand how the algorithmic traders help to incorporate information into prices with accuracy and speed when the market is volatile. Therefore, during the volatile period, which is in October 2016, I investigated the effect of algorithmic trading and price efficiency. The multivariate regression model is defined as:

$$SD(Pricing\ Error)_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \beta_5 TURNOVER_{it} + \varepsilon_{it} \quad (5.13)$$

The model is to test the null hypothesis which is there is no relationship between algorithmic trading and price efficiency:

H_0: All β_1 = 0

H_a: β_1 is not equal to 0.

Similar to the earlier methods, I used the pooled ordinary least square, the fixed effects model and the random effects model to test the null hypothesis for both models. Then, the restricted F-test and the Hausman test are used to select the proper model.

5.3.4 Model Extension

Similar to the previous section, I extended the algorithmic trading proxy to compute the algorithmic trading initiated by the institutional and foreign investors. I reckoned that most of algorithmic trading traffic are generated by institutional and foreign investors due to their access to the direct market access (DMA) and their technological investment. Therefore, algorithmic trading initiated by institutional investors is calculated by:

$$AT_{it}^{I} = \frac{-V_{it}^{I}}{MT_{it}^{I}} \tag{5.14}$$

And, the daily algorithmic trading initiated by foreign investors is measured as:

$$AT_{it}^{F} = \frac{-V_{it}^{F}}{MT_{it}^{F}} \tag{5.15}$$

where AT_{it}^{I} and AT_{it}^{F} are the proxies for the algorithmic trading initiated by institutional and foreign investors respectively. V_{it}^{I} and V_{it}^{F} are the trading volumes in Thai Baht initiated by institutional and foreign investors respectively. MT_{it}^{I} and MT_{it}^{F} are the message traffic for stock i on day t by institutional and foreign investors respectively.

As algorithmic trading initiated by institutional and foreign investors take place synchronously, I included the interaction term into the model as well. Consequently, the multivariate regression models can be written as:

$$SD(Pricing\ Error)_{it} = \alpha + \beta_1 AT_{it}^{I} + \beta_2 AT_{it}^{F} + \beta_3 AT_{it}^{I} AT_{it}^{F} + \beta_4 VOLATILITY_{it} + \beta_5 \left(\frac{1}{PRICE}\right)_{it} + \beta_6 LN(MARKET\ CAP)_{it} + \beta_7 TURNOVER_{it} + \varepsilon_{it} \tag{5.25}$$

This specification is used to test the following null hypothesis.

H_0: $\beta_1 = \beta_2 = \beta_3 = 0$

H_a: β_1, β_2, β_3 are not equal to 0.

5.3.5 Descriptive Statistics

I eliminated all the stocks with incomplete data and eliminated the 2.5% outliers. The descriptive statistics is shown in Table 5.2. On average, the standard deviation of the pricing error is 0.0147. The mean algorithmic trading proxy is -37.4513 and the standard deviation of 28.2685. Furthermore, the mean algorithmic trading initiated by institutional investors is -89.1487 with the standard deviation of 80.1204. Additionally, the average value of the algorithmic trading initiated by foreign investors proxy is -35.1460 and its standard deviation is equal to 37.8699.

Table 5.2 Descriptive Statistics

Variables	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Standard deviation of pricing error	0.0147	0.0105	0.0147	0.0002	0.2236
Algorithmic trading proxy (all)	-37.4513	-29.1201	28.2685	-141.7540	-1.0417
Algorithmic trading proxy (institutional investors)	-89.1487	-65.6454	80.1204	-762.6927	-0.0037
Algorithmic trading proxy (foreign investors)	-35.1460	-21.8087	37.8699	-405.3131	-0.0021
Control Variables					
Natural logarithm of market capitalization	14.1114	14.0692	1.2268	8.2669	17.2062
Realized volatility (%)	0.4103	0.3932	0.1526	0	3.1380
Share turnover	0.0047	0.0026	0.0079	2.3600x10-5	0.3259
The inverse of share price (1/Baht)	0.1092	0.0517	0.1398	0.0019	0.9302

To provide the linkage of the effect of algorithmic trading on price efficiency during the volatile period, the dataset during October 2016 is employed. The descriptive statistics during that period is summarized in Table 5.3. The standard deviation of pricing error averages at 0.0148. The algorithmic trading proxy has the average of -38.7764 with the standard deviation of 28.2461. The algorithmic trading initiated by institutional and foreign investors proxies have the mean value of -90.2951 and -34.9389 with the standard deviation of 79.6655 and 356989 respectively.

Table 5.3 Descriptive Statistics for the Volatile Period

Variables	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Standard deviation of pricing error	0.0148	0.0109	0.0136	0.0007	0.1544
Algorithmic trading proxy (all)	-38.7764	-31.2157	28.2461	-141.7540	-2.1917
Algorithmic trading proxy (institutional investors)	-90.2951	-67.2761	79.6655	-472.4223	-0.0246
Algorithmic trading proxy (foreign investors)	-34.9389	-21.8977	35.6989	-266.9184	-0.0393
Control Variables					
Natural logarithm of market capitalization	14.0997	14.0020	1.2225	8.2669	17.2062
Realized volatility (%)	0.4621	0.4166	0.2506	0.1334	3.1380
Share turnover	00054	0.0031	0.0074	$6.76x10^{-5}$	0.0681
The inverse of share price (1/Baht)	0.1135	0.0529	0.1463	0.0019	0.8249

5.4 Results and Discussion

5.4.1 Correlation Analysis

Table 5.4 displays the correlation analysis. Algorithmic trading is positively correlated with the standard deviation of the pricing error ($r(19295) = 0.278$ and $p < 0.01$). Correspondingly, algorithmic trading initiated by institutional and foreign investors have the positive correlation with the standard deviation of the pricing error with the coefficient of 0.187 and 0.175 respectively. The control variables are positively correlated with realized volatility and the inverse of price and negatively correlated with the natural logarithm of the market capitalization and the share turnover.

Table 5.4 Correlation Matrix. *, ** and *** Denote Significance at the 10%, 5% and 1% Level

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. SD of pricing error	1							
2. Algorithmic trading (all)	0.278***	1						
3. Algorithmic trading initiated by institutional investors	0.187***	0.830***	1					
4. Algorithmic trading initiated by foreign investors	0.175***	0.812***	0.630***	1				
5. Volatility	0.284***	0.062***	0.035***	0.083***	1			
6. Inverse of average price	0.510***	0.307***	0.226***	0.193***	0.141***	1		
7. Natural logarithm of market capitalization	-0.238***	-0.620***	-0.552***	-0.549***	-0.197***	-0.310***	1	
8. Share turnover	-0.053***	-0.263***	-0.225***	-0.243***	0.319***	0.094***	-0.112***	1

Table 5.5 displays the correlation analysis during the volatile period. First, the correlation between algorithmic trading and the standard deviation of the pricing error is 0.259 with the confidence level of 99%. Second, the standard deviation of the pricing error are positively correlated with algorithmic trading initiated by institutional ($r(1906) = 0.199$ and $p < 0.01$) and foreign investors ($r(1906) = 0.146$ and $p < 0.01$) respectively. Third, the control variables exhibit the appropriate correlation signs with the standard deviation of the pricing error. The standard deviation of the pricing error is positively correlated with realized volatility and the inverse of the average price. The natural logarithm of market capitalization has a negative correlation with the standard deviation of the pricing error. Furthermore, there is no correlation between share turnover and the natural logarithm of market capitalization.

Table 5.5 Correlation Matrix during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level

	1	2	3	4	5	6	7	8
1. SD of pricing error	1							
2. Algorithmic trading (all)	0.259***	1						
3. Algorithmic trading initiated by institutional investors	0.199***	0.865***	1					
4. Algorithmic trading initiated by foreign investors	0.146***	0.794***	0.653***	1				
5. Volatility	0.347***	0.018	0.022	0.042*	1			
6. Inverse of average price	0.504***	0.304***	0.241***	0.165***	0.120***	1		
7. Natural logarithm of market capitalization	-0.238***	-0.616***	-0.581***	-0.560***	-0.173***	-0.332***	1	
8. Share turnover	0.0203	-0.263***	-0.239***	-0.213***	0.352***	0.235***	-0.185***	1

5.4.2 The Effect and The Causal Relationship of Algorithmic Trading Proxy on Price Efficiency

The regression coefficients are estimated using various estimation techniques as depicted in Table 5.6 (I included all variables as there is no multicollinearity problem – See appendix C-2 for the test). The result from Table 5.6 reveals that in some estimation models, the coefficients of the algorithmic trading proxy on the standard deviation of pricing error are significant whereas in other estimation models, the coefficients are insignificant. The plot of the mean, the restricted F-test and the Hausman test are used to determine the proper model (See appendix C-3 to C-5). Therefore, these two tests demonstrate that the two-way fixed-effect model is the best-fitted model. The regression analysis connotes that there is no relationship between the algorithmic trading proxy and price efficiency.

Table 5.6 Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Standard Deviation of Pricing Error using the Pooled OLS, Individual Fixed-effects, Time Fixed-effects, Twoways Fixed-effects, Individual Random-effects and Time Random-effects Estimation Techniques. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

	Pooled OLS	**Individual Fixed-Effects**	**Time Fixed-Effects**	**Twoways Fixed-Effects**
Intercept	0.0058^{***}			
	(4.299)			
Algorithmic	$3.2165\text{x}10^{-5***}$	$9.2525\text{x}10^{-6}$	$2.9079\text{x}10^{-5***}$	$7.1396\text{x}10^{-6}$
trading	(7.284)	(1.620)	(6.564)	(1.227)
Volatility	0.0261^{***}	0.0169^{***}	0.0302^{***}	0.0205^{***}
	(42.663)	(24.520)	(45.336)	(26.002)
The inverse of	0.0498^{***}	0.0726^{***}	0.0497^{***}	0.0803^{***}
price	(74.489)	(14.697)	(74.984)	(15.986)
Natural log of	-0.0003^{***}		-0.0003^{***}	
market cap	(-3.046)		(-2.739)	

Table 5.6 (Continued)

	Pooled OLS	**Individual Fixed-Effects**	**Time Fixed-Effects**	**Twoways Fixed-Effects**
Share turnover	-0.3178	-0.2834***	-0.3219***	-0.2821***
	(-24.745)	(-18.974)	(-25.127)	(-18.830)
Adjusted R^2	34.15%	4.88%	34.56%	4.88%
	Individual Random Effects	**Time Random Effects**		
Intercept	0.0127**	0.0051***		
	(2.450)	(3.752)		
Algorithmic trading	1.4437×10^{-5}***	3.1132×10^{-5}***		
	(2.594)	(7.054)		
Volatility	0.0174***	0.0274***		
	(25.555)	(43.649)		
The inverse of price	0.0560***	0.0498***		
	(20.365)	(74.818)		
Natural log of market cap	-0.0006*	-0.0003***		
	(-1.743)	(-2.951)		
Share turnover	-0.2843***	-0.3191***		
	(-19.325)	(-24.909)		
Adjusted R^2	6.98%	34.53%		

An alternative method to assure the validity of our result is the two-stage least square analysis. Using the instrumental variable, the 2SLS result is presented in Table 5.7. The first regression demonstrates that there is a relationship between algorithmic trading and instrumental variable. The second-stage regression furnishes identical outcome which is that there is no relationship between algorithmic trading and price efficiency.

Table 5.7 2SLS Analysis for the Impact of Algorithmic Trading Proxy on Price Efficiency. *, ** and *** Denote Significance at the 10%, 5% and 1%.

Variable	**First Stage Algorithmic Trading**	**Second Stage Standard deviation of pricing error**
Intercept	157.6557***	0.00390
	(76.673)	(1.011)
Instrumental Variable	0.8621**	
	(2.563)	
Algorithmic trading		-1.8131×10^{-4}
		(-0.742)
Volatility	-13.5453***	0.0181***
	(-13.043)	(5.368)
The inverse of price	26.9689***	0.0549***
	(23.063)	(8.273)
Natural log of market cap	-13.6597***	-0.0031
	(-101.555)	(-0.938)
Adjusted R-squared	40.39%	17.83%

5.4.3 The Effect of Algorithmic Trading Initiated by Institutional and Foreign Investors on Price Efficiency

As the algorithmic trading proxy may incorporate the message traffic from retail investors who also involve in submitting small-sized orders, I segregated the result by investigating the effect of algorithmic trading initiated by institutional and foreign investors on price efficiency. Table 5.8 illustrates the regression coefficients assessed by various methods. The pooled OLS slope coefficient of algorithmic trading initiated by foreign investors and the interaction term between algorithmic trading initiated by institutional and foreign investors are significantly negative.

I selected the two-way fixed-effect estimation method to compute the relationship between algorithmic trading initiated by institutional and foreign investors and price efficiency (See appendix C-6 to C-8 for the selection tests). From the Table

5.8, the two-way fixed-effect model indicates that there are negative relationships between the algorithmic trading proxies and the standard deviation of pricing error. The slope coefficient of algorithmic trading initiated by institutional investors on the standard deviation of pricing error is $-3.6473x10^{-6}$ with the t-value of -1.713. Therefore, when algorithmic trading initiated by institutional investors increases by one standard deviation, the pricing error decreases by 0.00029 standard deviation or 1.99 percent from the mean of the standard deviation of the pricing error. In addition, the standard deviation of the pricing error diminishes by 0.00059 or 4.01 percent from the average of the standard deviation of the pricing error due to an increase in algorithmic trading initiated by foreign investors by one standard deviation. The interaction between algorithmic trading initiated by institutional and foreign investors also declines by 0.00014 or 0.95 percent from the average of the standard deviation of the pricing error due to the increase in the interaction term by one standard deviation. Therefore, increases in the algorithmic trading initiated by institutional and foreign investors proxies and their interaction term reduce the standard deviation of the pricing error and therefore, increase price efficiency.

Table 5.8 Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxy and Control Variables on Standard Deviation of Pricing Error Using the Pooled OLS, Individual Fixed-effects, Time Fixed-effects, Twoways Fixed-effects, Individual Random-effects And Time Random-effects Estimation Techniques. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

	Pooled OLS	**Individual Fixed-Effects**	**Time Fixed-Effects**	**Twoways Fixed-Effects**
Intercept	0.0091^{***} (6.742)			
AT initiated by institutional investors	$-7.5794x10^{-7}$ (-0.378)	$-5.2287x10^{-6**}$ (-2.491)	$1.1904x10^{-6}$ (0.590)	$-3.6473x10^{-6*}$ (-1.713)

Table 5.8 (Continued)

	Pooled OLS	**Individual Fixed-Effects**	**Time Fixed-Effects**	**Twoways Fixed-Effects**
AT initiated by foreign investors	$-1.6536\text{x}10^{-5***}$	$-1.8677\text{x}10^{-5***}$	$-1.3428\text{x}10^{-5***}$	$-1.5592\text{x}10^{-5***}$
	(-3.319)	(-3.659)	(-2.662)	(-2.992)
Interaction term	$-4.3083\text{x}10^{-8*}$	$-6.0099\text{x}10^{-8**}$	$-2.1068\text{x}10^{-8}$	$-4.5822\text{x}10^{-8*}$
	(-1.732)	(-2.355)	(-0.847)	(-1.789)
Volatility	0.0270^{***}	0.0169^{***}	0.0313^{***}	0.0206^{***}
	(45.225)	(25.102)	(48.098)	(26.664)
The inverse of price	0.0524^{***}	0.0781^{***}	0.0521^{***}	0.0849^{***}
	(79.738)	(15.505)	(79.917)	(16.613)
Natural log of market cap	-0.0007^{***}		-0.0006^{***}	
	(-7.180)		(-5.977)	
Share turnover	-0.3555^{***}	-0.3086^{***}	-0.3540^{***}	-0.3015^{***}
	(-28.704)	(-21.530)	(-28.639)	(-20.923)
Adjusted R^2	35.98%	5.20%	36.46%	4.52%

	Individual Random-Effects	**Time Random-Effects**
Intercept	0.0150^{***}	0.0082^{***}
	(3.153)	(6.068)
AT initiated by institutional investors	$-3.7220\text{x}10^{-6*}$	$-1.8488\text{x}10^{-7}$
	(-1.795)	(-0.092)
AT initiated by foreign investors	$-1.5365\text{x}10^{-5***}$	$-1.5629\text{x}10^{-5***}$
	(-3.040)	(-3.130)

Table 5.8 (Continued)

	Individual Random-Effects	**Time Random-Effects**
Interaction	$-4.8324\text{x}10^{-8*}$	$-3.6754\text{x}10^{-8}$
Term	(-1.908)	(-1.479)
Volatility	0.0176^{***}	0.0282^{***}
	(26.381)	(46.098)
The inverse	0.0570^{***}	0.0523^{***}
of price	(22.032)	(79.929)
Natural log	-0.0009^{***}	-0.0007^{***}
of market	(-2.695)	(-6.847)
cap		
Share	-0.3121^{***}	-0.3549^{***}
turnover	(-22.136)	(-28.713)
Adjusted R^2	7.71%	36.31%

5.4.4 The Effect of Algorithmic Trading on Price Efficiency during the Volatile Period

I developed the empirical test using the multiple regression analysis in order to explore the relationship between algorithmic trading and price efficiency during the volatile period. Therefore, I implemented equation 5.13:

$$SD(Pricing\ Error)_{it} = \alpha + \beta_1 AT_{it} + \beta_2 VOLATILITY_{it} + \beta_3 \left(\frac{1}{PRICE}\right)_{it} + \beta_4 LN(MARKET\ CAP)_{it} + \varepsilon_{it} \tag{5.13}$$

Clearly, there is a relationship between algorithmic trading and price efficiency during the volatile period, as demonstrated in Table 5.9. All of the coefficients divulge a positive relationship between the standard deviation of the pricing error and the algorithmic trading proxy with the coefficient between $4.3653\text{x}10^{-5}$ and $7.4401\text{x}10^{-5}$. Consequently, three tests are conducted to identify the proper model to use and found that the two-way fixed-effect model is the most appropriate model (See appendix C-9 to C-11).

The coefficient of algorithmic trading on the standard deviation of the pricing error during the volatile period is 5.1465x10^{-5}. Thusly, one standard deviation increase in algorithmic trading implies an increase in the standard deviation of the pricing error by 0.0015 or 9.82 percent from the mean value of the standard deviation of the pricing error during the volatile period. Thus, algorithmic trading decreases price efficiency during the volatile period.

Table 5.9 Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Standard Deviation of Pricing Error Using the Pooled OLS, Individual Fixed-effects, Time Fixed-effects, Twoways Fixed-effects, Individual Random-effects And Time Random-effects Estimation Techniques during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

	Pooled OLS	**Individual Fixed-Effects**	**Time Fixed-Effects**	**Twoways Fixed-Effects**
Intercept	-0.0032			
	(-0.865)			
Algorithmic	7.4401x10^{-5***}	4.5270x10^{-5***}	7.3719x10^{-5***}	5.1465x10^{-5***}
Trading	(6.550)	(2.809)	(6.436)	(3.002)
Volatility	0.0163***	0.0121***	0.0215***	0.0133***
	(16.078)	(11.429)	(15.351)	(8.849)
The inverse of	0.0409***	-0.0011	0.0406***	0.0035
price	(22.420)	(-0.042)	(22.474)	(0.122)
Natural log of	0.0006**		0.0008***	
market cap	(2.303)		(2.809)	
Adjusted R^2	35.17%	2.30%	34.59%	-1.85%

Table 5.9 (Continued)

	Individual Random-Effects	Time Random-Effects
Intercept	0.0037	-0.0042
	(0.541)	(-1.140)
Algorithmic	$5.5353\text{x}10^{-5***}$	$7.4798\text{x}10^{-5***}$
Trading	(3.906)	(6.573)
Volatility	0.0126^{***}	0.0175^{***}
	(12.858)	(15.736)
The inverse	0.0408^{***}	0.0408^{***}
of price	(10.740)	(22.471)
Natural log	0.0002	0.0007^{**}
of market	(0.397)	(2.445)
cap		
Adjusted R^2	15.01%	35.10%

5.4.5 The Effect of Algorithmic Trading Initiated by Institutional and Foreign Investors on Price Efficiency during the Volatile Period

To delve further, I explored the effect of algorithmic trading initiated by institutional and foreign investors on price efficiency during the volatile period. Therefore, I employed various estimation techniques and listed the regression coefficients in Table 5.10. Like the previous section, I used the result from the two-ways fixed-effect model and found that there is no relationship between all algorithmic trading proxies and the standard deviation of pricing error during the volatile period. This is important as it shows that a decrease in price efficiency is not due to algorithmic trading initiated by institutional and foreign investors.

Table 5.10 Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxy and Control Variables on Standard Deviation of Pricing Error Using the Pooled OLS, Individual Fixed-effects, Time Fixed-effects, Twoways Fixed-effects, Individual Random-effects And Time Random-effects Estimation Techniques during the Volatile Period. *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

	Pooled OLS	**Individual Fixed-Effects**	**Time Fixed-Effects**	**Twoways Fixed-Effects**
Intercept	-0.0022			
	(-0.565)			
AT initiated by institutional investors	$1.5467\text{x}10^{-5**}$	$2.3227\text{x}10^{-7}$	$1.8534\text{x}10^{-5***}$	$2.9779\text{x}10^{-6}$
	(2.490)	(0.034)	(2.970)	(0.419)
AT initiated by foreign investors	$7.4231\text{x}10^{-6}$	$-1.8813\text{x}10^{-5}$	$2.0599\text{x}10^{-5}$	$-9.1544\text{x}10^{-6}$
	(0.509)	(-1.223)	(1.394)	(-0.578)
Interaction Term	$-3.7537\text{x}10^{-10}$	$-1.5494\text{x}10^{-7*}$	$6.7452\text{x}10^{-8}$	$-1.1776\text{x}10^{-7}$
	(-0.005)	(-1.868)	(0.849)	(-1.402)
Volatility	0.0016^{***}	0.0122^{***}	0.0217^{***}	0.0134^{***}
	(15.865)	(11.459)	(15.352)	(8.909)
The inverse of price	0.0439^{***}	-0.0193	0.0436^{***}	-0.0140
	(23.585)	(-0.644)	(23.624)	(-0.429)
Natural log of market cap	0.0004		0.0007^{**}	
	(1.552)		(2.325)	
Adjusted R^2	35.32%	2.59%	34.75%	-1.91%

Table 5.10 (Continued)

	Individual Random-Effects	Time Random-Effects
Intercept	0.0058 (0.849)	-0.0027 (-0.698)
AT initiated by institutional investors	3.7853×10^{-6} (0.575)	$1.5870 \times 10^{-5**}$ (2.554)
AT initiated by foreign investors	-1.1997×10^{-5} (-0.810)	9.0971×10^{-6} (0.622)
Interaction term	-1.1981×10^{-7} (-1.495)	7.5568×10^{-9} (0.096)
Volatility	0.0124^{***} (12.769)	0.0167^{***} (15.722)
The inverse of price	0.0042^{***} (11.206)	0.0438^{***} (23.610)
Natural log of market cap	-7.8338×10^{-5} (1.665)	0.0005 (1.161)
Adjusted R^2	15.51%	35.27%

5.5 Conclusion

This chapter examines the impact of algorithmic trading on price efficiency in the Stock Exchange of Thailand. I implemented the multiple regression analysis. Two concerns arise including the multicollinearity and the heterogeneity issues. To eliminate heterogeneity, I implemented two-way fixed-effect regression analysis techniques. Furthermore, I conducted the two-stage least squares in order to establish the causality. It is interesting to understand the role of algorithmic trading on price efficiency during the volatile period. Therefore, I conducted the empirical testing during the volatile period. Furthermore, I introduced the algorithmic trading initiated by institutional and foreign investors proxies to establish the relationship with price efficiency.

The empirical testing indicates that there is no relationship between algorithmic trading and price efficiency. I found negative relationships between the algorithmic trading initiated by institutional and foreign investors proxies and the standard deviation of pricing error-algorithmic trading initiated by institutional and foreign investors decrease pricing error. This is similar to the results by Brogaard et al. (2014) and Hendershott and Riordan (2009). Therefore, algorithmic trading initiated by institutional and foreign investors behave like informed investors, helping to improve price efficiency. Furthermore, the effect of algorithmic trading initiated by foreign investors on price efficiency is higher than the effect of algorithmic trading initiated by institutional investors on price efficiency. Overall, algorithmic trading has a beneficial role in improving price efficiency in term of achieving smaller pricing error. However, during the volatile period, the role of algorithmic trading on price efficiency is switched. It hinders price efficiency when the market is volatile; however, this is not because of algorithmic trading initiated by institutional and foreign investors. Algorithmic trading by institutional and foreign investors improve market quality by increasing price efficiency; however, when the market is volatile, their effects evaporate.

CHAPTER 6

CONCLUSION

Chapter 3, 4 and 5 examine the effect of three algorithmic trading proxies on market quality i.e. volatility, liquidity and price efficiency. The models establish the causal relationship between algorithmic trading and volatility and liquidity, but not price efficiency. Algorithmic trading causes realized volatility and range-based volatility to decrease. When investigating the effect of algorithmic trading on volatility for each stock, in seventy-five percent of the stocks, algorithmic trading is associated with positive volatility and in the stocks where the regression coefficients are negative, the magnitude of coefficients are higher. Though algorithmic trading aggregately decreases volatility, it leads a larger portion of stocks to have higher volatility. Furthermore, algorithmic trading causes liquidity to be lower by widening effective spread and lowering share turnover. In the long run, algorithmic trading also deters liquidity by reducing liquidity ratio. Aggregately, there is no relationship between algorithmic trading and price efficiency.

I further showed that the introduction of two additional algorithmic trading proxies could improve the comprehension of the effect of algorithmic trading on market quality. They are the algorithmic trading initiated by institutional investors proxy and the algorithmic trading initiated by foreign investors proxy. It is found that the average algorithmic trading initiated by foreign investors proxy is higher than the average algorithmic trading initiated by institutional investors proxy.

Algorithmic trading initiated by institutional and foreign investors and their interaction reduce volatility. However, they increase effective spread and Amihud's illiquidity estimate and reduce share turnover. Contradicting to the effect of aggregate algorithmic traders on price efficiency, algorithmic trading initiated by institutional and foreign investors and their interaction decrease pricing error, causing an improve in price efficiency. I also found that algorithmic trading initiated by institutional investors has higher effects in reducing volatility and long-term liquidity than algorithmic trading initiated by foreign investors has. On the other hand, algorithmic trading initiated by foreign investors has higher effects in distorting short-term liquidity and increasing price efficiency than algorithmic trading initiated by institutional investors has, confirming the research by Kim and Yi (2015) and Seashole (2004) that foreign investors possess superior information.

This may assert that algorithmic trading initiated by each type of investors is a better proxy to measure the effect of algorithmic trading on market quality as retail investors may exhibit the behaviors that are similar to algorithmic traders because their orders are small, but not fast. However, retail investors are often noise traders and their trade carry less information.

In addition, I found that the effect of algorithmic trading on some parameters of the market quality changes when the market volatility changes. During the high-volatility period, algorithmic trading also reduces range-based volatility. However, I do not find any evidence that algorithmic trading affects realized volatility during the high-volatility period. Furthermore, algorithmic trading increases effective half spread, lowers share turnover and reduces liquidity ratio and exerts no impact on the Amihud's illiquidity estimate. The magnitude of the effect of algorithmic trading on range-based volatility and liquidity is higher during the volatile period than during all periods. On the contrary, the effect of algorithmic trading on price efficiency is reverse when the market volatility is high. Algorithmic trading decreases price efficiency during the volatile period.

During the volatile period, algorithmic trading initiated by foreign investors plays more roles in lowering realized volatility than algorithmic trading initiated by institutional investors does. Likewise, during the volatile period, algorithmic trading initiated by foreign investors plays more role in distorting liquidity in term of enlarged effective spread and share turnover.

In conclusion, the results reveal that algorithmic traders are informed investors. On the other words, even when the informed investors such as institutional and foreign investors use technology to execute their order, their informational advantages do not change. They help to lower volatility and improve price efficiency. However, their participation increases information asymmetry and imposes adverse selection risks onto other traders. In response of higher risks, slower traders cease to participate in the stock, resulting in lower share turnover. The presence of algorithmic traders conveys more information in prices, reducing pricing error and volatility.

This study has some limitations due to the unavailability of the data. One is that as algorithmic trading activity is a proprietary data and is not directly observable, I used the proxy to estimate the amount of algorithmic trading instead. Second, the use of the normalized traffic message proxy reports only the aggregate data on the algorithmic trading activities. This, therefore, include all types of algorithmic trading strategies. As a result, the impact of algorithmic trading on the market quality might be dominant by certain type of algorithmic trading strategy (Biais & Foucault, 2014). Furthermore, as I utilized the normalized traffic message or the order-to-trade ratio as the measurement of algorithmic trading activities, this measurement might be biased as it focuses on certain attributes of algorithmic trading strategies. As the proprietary high frequency traders who consume liquidity tend to have a lower AT proxy than the market-making frequency traders who supply liquidity (Hagströmer & Nordén, 2013), the effect of algorithmic trading on market quality using the normalized traffic messages may provide more positive effect than actuality.

Fourth, is that the study is conducted on the SET100 only and during the period of March to December 2016. Finally, due to the unavailability of the data, this study does not report the brokerage data. This research shed the light on the effect of algorithmic trading on market quality, which is particularly useful for regulators and investors. Future studies may be conducted to link the effect of algorithmic trading on asset pricing.

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APPENDICES

APPENDIX A

THE IMPACT OF ALGORITHMIC TRADING ON VOLATILITY

APPENDIX A

THE IMPACT OF ALGORITHMIC TRADING ON VOLATILITY

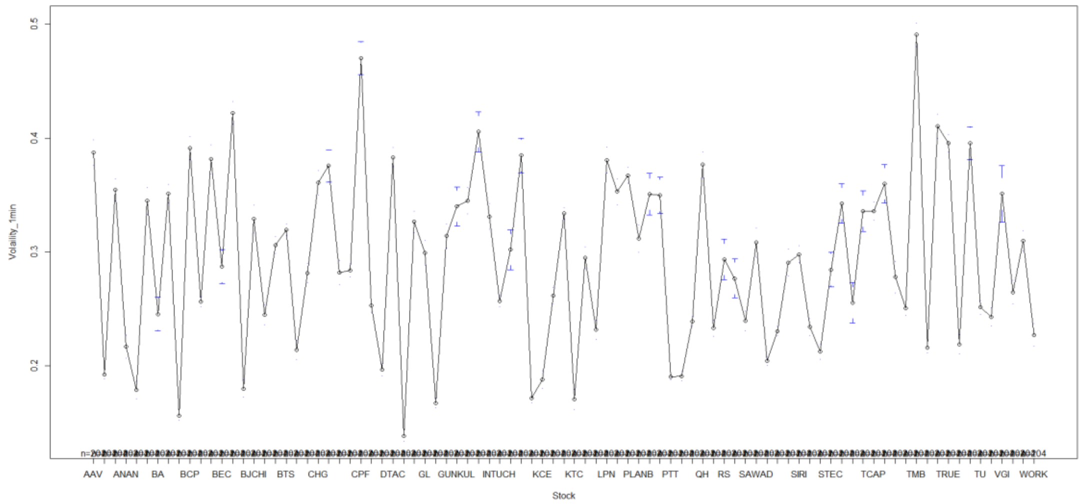
Appendix A-1 Multicollinearity Problem

The variance inflation factor (VIF) is computed to detect the multicollinearity. As all the scores of the VIF is lower than five, there is no evidence that there is multicollinearity in the variables.

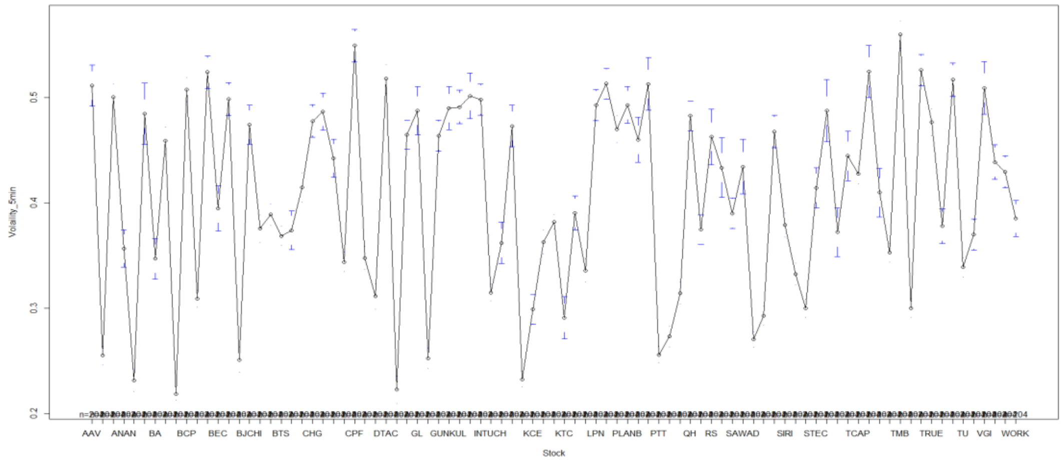
Algorithmic Trading	Price-to-book Ratio	Share Turnover	Inverse of Price	Effective Half Spread	Natural Log of Market Cap
2.5400	1.0154	1.3097	1.1855	1.1403	2.3621

Appendix A-2 Heterogeneity in the Volatility Data

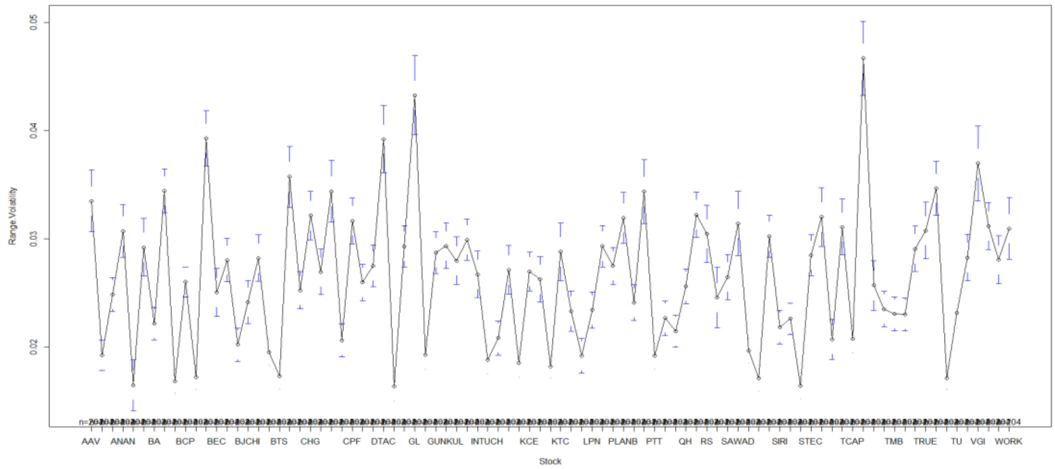
The mean plot of the one-minute realized volatility across individual



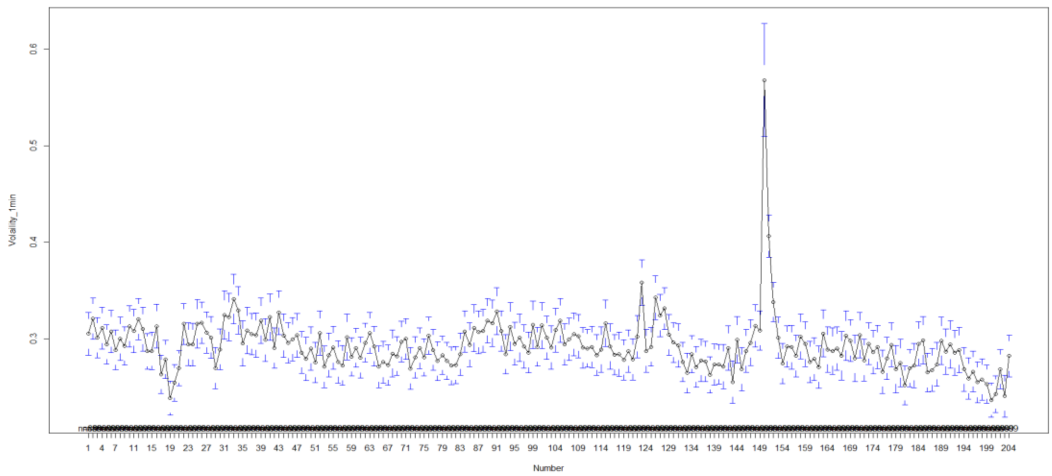
The mean plot of the five-minute realized volatility across individual



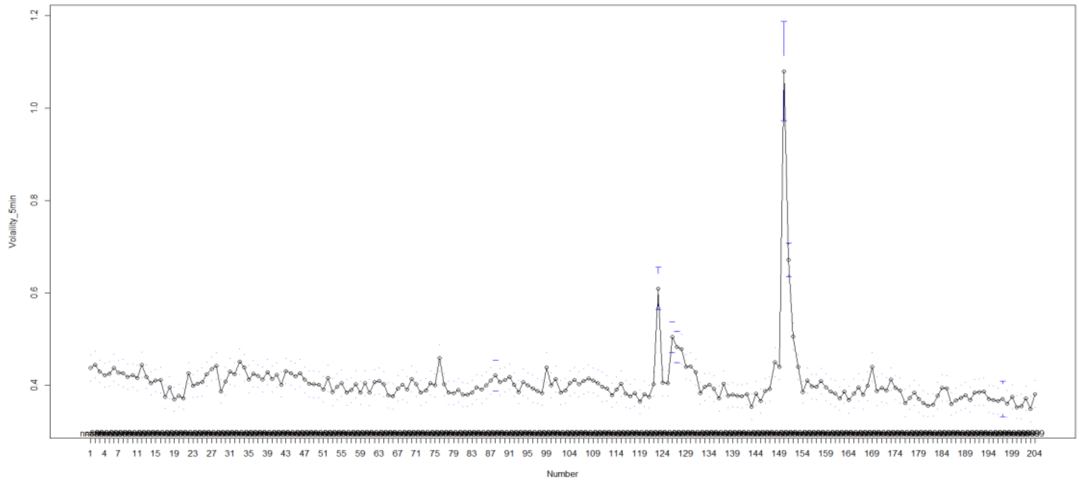
The mean plot of the range-based volatility across individual



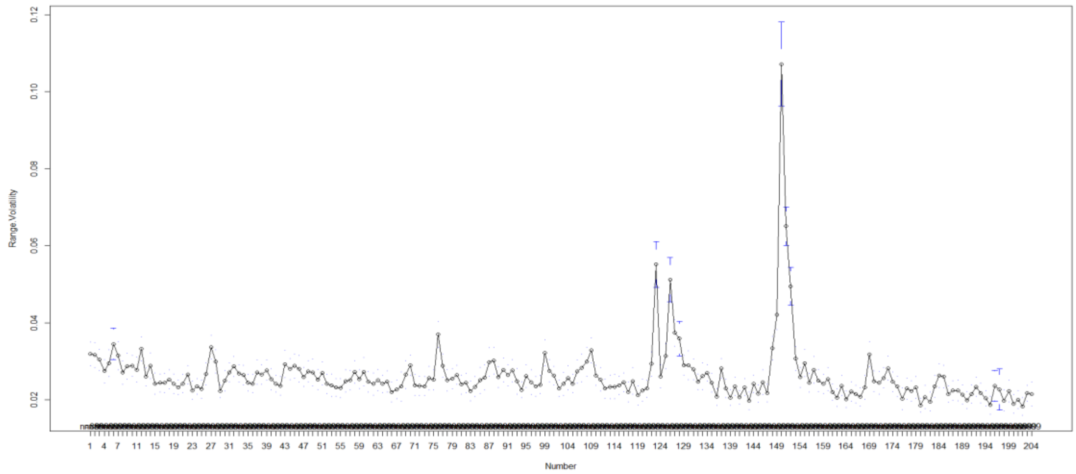
The mean plot of the one-minute realized volatility across time



The mean plot of the five-minute realized volatility across time



The mean plot of the range-based volatility across time



Appendix A-3 Restricted F-Tests

The restricted F-test for individual, time and two-way effects are displayed below, confirming that the two-way fixed-effect model is a better choice than the pooled OLS model.

Restricted F-test for Individual Effects

	Model 1	Model 2	Model 3
F-statistics	53.056	33.501	32.343
p-value	< 0.01	< 0.01	< 0.01

Restricted F-test for Time Effects

	Model 1	Model 2	Model 3
F-statistics	54.473	37.869	34.152
p-value	< 0.01	< 0.01	< 0.01

Restricted F-test for Individual and Time Effects

	Model 1	Model 2	Model 3
F-statistics	32.258	40.123	38.165
p-value	< 0.01	< 0.01	< 0.01

Appendix A-4 Chi-square Statistics for Individual and Time Effects

	Model 1	Model 2	Model 3
		Individual	
F-statistics	126.890	162.050	163.100
p-value	< 0.01	< 0.01	< 0.01
		Time	
F-statistics	570.600	69.020	64.217
p-value	< 0.01	< 0.01	< 0.01
		Two ways (Individual and Time)	
F-statistics	1185.600	2309.800	133.000
p-value	< 0.01	< 0.01	< 0.01

Appendix A-5 Regression Coefficients

Within-group (Individual) Fixed-effect Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Volatility Measures.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
AT_{it}	$-1.8263 \times 10^{-4***}$	$-3.5488 \times 10^{-4***}$	$-3.8392 \times 10^{-5***}$
	(-7.571)	(-8.378)	(-7.321)
Price-to-book ratio	0.0050^{***}	0.0034^{***}	0.0003^{**}
	(8.464)	(3.313)	(2.528)
Share turnover	5.0074^{***}	8.4570^{***}	1.5827^{***}
	(47.868)	(46.042)	(69.599)
The inverse of	0.1168^{***}	0.4444^{***}	0.0658^{***}
price	(3.874)	(8.399)	(10.047)
Effective half	0.5351^{***}	0.5007^{***}	-0.0054^{***}
spread	(118.642)	(63.228)	(-5.500)
Natural log of market cap			
Adjusted R^2	47.04%	26.07%	29.57%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Within-group (Time) Fixed-effect Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Volatility Measures.

Variable	**Model 1 1-minute realized volatility**	**Model 2 5-minute realized volatility**	**Model 3 Range-based volatility**
AT_{it}	$8.9937 \times 10^{-5***}$	$-9.9744 \times 10^{-5***}$	-5.8968×10^{-6}
	(4.582)	(-3.249)	(-1.565)
Price-to-book ratio	0.0020^{***}	0.0039^{***}	0.0007^{***}
	(15.526)	(19.860)	(27.303)
Share turnover	6.2164^{***}	7.9812^{***}	1.2971^{***}
	(69.082)	(56.694)	(75.064)
The inverse of	0.0513^{***}	-0.0064	-0.0057^{***}
price	(14.335)	(-1.144)	(-8.332)
Effective half	0.6479^{***}	0.6392^{***}	-0.0006
spread	(171.027)	(107.844)	(0.374)
Natural log of	0.0081^{***}	-0.0216^{***}	-0.0018^{***}
market cap	(12.980)	(-21.970)	(-15.174)
Adjusted R^2	67.02%	51.18%	32.02%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Random-effect (Individual) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Volatility Measures.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
Intercept	0.1013***	0.5417***	0.0389***
	(3.031)	(10.045)	(5.642)
AT_{it}	-1.7261×10^{-4}***	-3.2215×10^{-4}***	-3.3571×10^{-5}***
	(-7.243)	(-7.724)	(-6.489)
Price-to-book ratio	0.0036***	0.0024***	0.0003***
	(8.279)	(3.249)	(2.875)
Share turnover	5.1020***	8.3988***	1.5577***
	(49.219)	(46.263)	(69.195)
The inverse of price	0.0817*** (5.160)	0.1237*** (4.763)	0.0141*** (4.261)
Effective half spread	0.5416*** (121.030)	0.5092*** (64.972)	-0.0051*** (-5.278)
Natural log of market cap	-0.0005 (-0.208)	-0.0242*** (-6.534)	-0.0015*** (-3.201)
Adjusted R^2	48.22%	27.33%	29.54%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Random-effect (Time) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Volatility Measures.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
Intercept	-0.0360***	0.4876***	0.0450***
	(-4.061)	(34.844)	(26.205)
AT_{it}	$8.4132x10^{-5}$***	$-1.0148x10^{-4}$***	$-6.2025x10^{-6}$
	(4.265)	(-3.285)	(-1.633)
Price-to-book ratio	0.0020***	0.0039***	0.0007***
	(15.342)	(19.648)	(26.957)
Share turnover	6.3262***	8.0712***	1.3100***
	(69.949)	(56.982)	(75.209)
The inverse of price	0.0518***	-0.0059	-0.0057***
	(14.346)	(-1.043)	(-8.161)
Effective half spread	0.6473***	0.6382***	-0.0007
	(169.922)	(107.005)	(-0.953)
Natural log of market cap	0.0081***	-0.0216***	-0.0018***
	(12.796)	(-21.804)	(-15.018)
Adjusted R^2	66.93%	51.17%	32.57%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Random-effect (Two-ways) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Volatility Measures.

Variable	**Model 1 1-minute realized volatility**	**Model 2 5-minute realized volatility**	**Model 3 Range-based volatility**
Intercept	0.1272***	0.6078***	0.0473***
	(3.784)	(11.318)	(6.891)
AT_{it}	-1.4174x10^{-4}***	-2.9936x10^{-4}***	-3.0324x10^{-5}***
	(-6.257)	(-8.126)	(-6.627)
Price-to-book ratio	0.0049***	0.0053***	0.0007***
	(11.622)	(7.866)	(7.782)
Share turnover	4.3657***	6.8812***	1.3730***
	(44.512)	(43.152)	(69.327)
The inverse of price	0.0463***	0.0388	0.0035
	(2.957)	(1.546)	(1.100)
Effective half spread	0.5400***	0.5167***	-0.0048***
	(127.385)	(74.963)	(-5.598)
Natural log of market cap	-0.0020	-0.0285***	-0.0021***
	(-0.867)	(74.936)	(-4.382)
Adjusted R^2	49.93%	30.25%	29.55%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Appendix A-6 Regression Coefficients of Algorithmic Trading Proxy for Each Stock Using Ordinary Least Square Estimation Method

Stock	Model 1 1-min realized volatility	Model 2 5-min realized volatility
AAV	2.7931×10^{-5}	-0.0002
	(0.091)	(-0.391)
ADVANC	1.2248×10^{-5}	5.5545×10^{-5}
	(0.135)	(0.214)
AMATA	0.0036^{***}	0.0022^{*}
	(4.935)	(1.947)
ANAN	0.0006	0.0007
	(1.096)	(0.571)
AOT	-8.0441×10^{-6}	5.9424×10^{-5}
	(-0.135)	(0.493)
AP	0.0013^{**}	0.0011
	(2.177)	(0.581)
BA	-5.4315×10^{-5}	-2.9969×10^{-5}
	(-0.212)	(-0.064)
BANPU	-0.0006^{***}	-0.0009^{**}
	(-3.222)	(-2.231)
BBL	0.0002^{***}	0.0004^{***}
	(3.365)	(3.322)
BCP	0.0006	0.0001
	(1.273)	(0.169)
BDMS	2.7863×10^{-5}	0.0003^{**}
	(0.292)	(2.065)
BEAUTY	0.0011^{**}	0.0011
	(2.300)	(1.249)
BEC	0.0041^{***}	0.0062^{**}
	(2.858)	(2.235)

Appendix A-6 (Continued)

Stock	Model 1 1-min realized volatility	Model 2 5-min realized volatility
BEM	1.2636×10^{-5}	0.0015**
	(0.039)	(2.527)
BH	0.0004**	0.0009**
	(2.052)	(1.979)
BJCHI	0.0008	-0.0037
	(0.493)	(-1.063)
BLA	0.0014***	0.0015*
	(2.950)	(1.826)
BLAND	-0.0016***	-0.0022***
	(-3.688)	(-3.468)
BTS	0.0006	0.0013
	(1.123)	(1.304)
CBG	0.0003*	0.0010***
	(1.697)	(3.075)
CENTEL	0.0012**	0.0007
	(2.538)	(0.724)
CHG	-0.0004	-0.0009
	(-0.481)	(-0.763)
CK	-0.0008**	-0.0003
	(-2.296)	(-0.425)
CKP	-0.0002	-0.0031***
	(-0.352)	(-2.664)
CPALL	0.0003***	0.0005***
	(3.684)	(3.455)
CPF	-0.0003	-0.0005
	(-0.838)	(-1.040)

Appendix A-6 (Continued)

Stock	Model 1 1-min realized volatility	Model 2 5-min realized volatility
CPN	0.0009***	0.0014***
	(7.288)	(5.470)
DELTA	0.0011***	0.0018**
	(3.366)	(2.196)
DTAC	0.0001	-0.0003
	(0.279)	(-0.990)
EGCO	0.0004**	0.0011**
	(2.466)	(2.318)
EPG	-0.0006	-0.0009
	(-1.414)	(-1.085)
GL	-0.0007***	-0.0009
	(-2.702)	(-1.474)
GLOW	0.0014***	0.0029***
	(5.210)	(4.140)
GPSC	2.4093×10^{-5}	-0.0004
	(0.089)	(-0.927)
GUNKUL	0.0010**	0.0013*
	(2.359)	(1.751)
HANA	0.0046***	0.0065***
	(5.647)	(4.899)
HMPRO	9.4516×10^{-5}	0.0001
	(0.110)	(0.080)
ICHI	-0.0027**	-0.0050***
	(-2.135)	(-2.907)
INTUCH	0.0004***	0.0010***
	(3.128)	(4.292)

Appendix A-6 (Continued)

Stock	Model 1 1-min realized volatility	Model 2 5-min realized volatility
IRPC	-0.0011***	-0.0006
	(-2.618)	(-0.966)
ITD	-0.0001	0.0003
	(-0.179)	(0.181)
KBANK	0.0001**	0.0001
	(2.496)	(1.395)
KCE	0.0012***	0.0021***
	(4.361)	(3.068)
KKP	0.0005**	0.0013***
	(2.096)	(2.721)
KTB	0.0003	0.0002
	(1.264)	(0.537)
KTC	0.0017***	0.0035***
	(4.245)	(3.791)
LH	0.0012***	0.0030***
	(2.844)	(3.689)
LHBANK	$6.1090\text{x}10^{-5}$	-0.0011**
	(0.155)	(-2.068)
LPN	0.0016*	0.0004
	(1.756)	(0.267)
MAJOR	0.0029***	0.0030***
	(8.891)	(5.827)
MINT	0.0011***	0.0014**
	(3.798)	(2.465)
PLANB	-0.0003	-0.0017*
	(-0.660)	(-1.893)

Appendix A-6 (Continued)

Stock	Model 1 1-min realized volatility	Model 2 5-min realized volatility
PS	-0.0003	-0.0024**
	(-0.435)	(-2.132)
PTG	0.0011***	0.0029***
	(2.740)	(3.431)
PTT	0.0001	0.0003***
	(3.640)	(2.776)
PTTEP	-3.6627×10^{-5}	0.0003
	(-0.407)	(1.292)
PTTGC	0.0002	0.0004
	(1.836)	(1.333)
QH	-0.0004	-0.0016
	(-0.425)	(-1.308)
ROBINS	0.0012***	0.0019**
	(3.994)	(2.559)
RS	0.0003	0.0003
	(0.312)	(0.145)
S	-0.0004	-0.0022
	(-0.609)	(-1.469)
SAMART	-0.0005	-0.0015
	(-0.616)	(-1.118)
SAWAD	0.0004	0.0004
	(1.126)	(0.512)
SCB	0.0003***	0.0004***
	(4.358)	(2.817)
SCC	0.0003***	0.0006***
	(6.134)	(4.688)

Appendix A-6 (Continued)

Stock	Model 1 1-min realized volatility	Model 2 5-min realized volatility
SGP	-0.0001	-0.0001
	(-0.179)	(-0.127)
SIRI	-0.0027**	-0.0012
	(-2.311)	(-0.659)
SPALI	0.0009***	0.0012**
	(3.102)	(2.527)
SPCG	0.0008	0.0021
	(0.781)	(1.429)
STEC	-0.0010***	-0.0012**
	(-3.623)	(-2.475)
STPI	-0.0024***	-0.0055***
	(-3.906)	(-3.304)
SVI	0.0015*	0.0006
	(1.675)	(0.363)
TASCO	-0.0006	-0.0005
	(-1.203)	(-0.528)
TCAP	0.0008**	0.0008*
	(2.504)	(1.699)
THAI	-0.0008***	-0.0008
	(-3.089)	(-1.361)
THCOM	-0.0021***	-0.0028**
	(-4.294)	(-2.293)
TISCO	0.0012***	0.0021***
	(4.082)	(3.994)
TMB	-0.0004	0.0004
	(-0.872)	(0.599)

Appendix A-6 (Continued)

Stock	**Model 1** **1-min realized volatility**	**Model 2** **5-min realized volatility**
TOP	0.0003**	0.0007*
	(2.171)	(1.943)
TPIPL	-2.8097×10^{-5}	-0.0012**
	(-0.080)	(-2.055)
TRUE	-5.4497×10^{-5}	-0.0001
	(-0.326)	(-0.346)
TTCL	-0.0016***	-0.0034***
	(-3.553)	(-3.665)
TTW	0.0044***	0.0018
	(3.264)	(1.028)
TU	0.0003	0.0012***
	(1.338)	(2.990)
UNIQ	0.0005	0.0005
	(1.339)	(0.586)
VGI	-0.0005	-0.0020
	(-0.253)	(-1.069)
VNG	-0.0002	6.8724×10^{-5}
	(-0.336)	(0.073)
WHA	-0.0003	-0.0002
	(-0.560)	(-0.179)
WORK	-0.0004	-0.0004
	(-1.345)	(-0.667)

Appendix A-7 Choi (2001)'s z Statistics for Panel Unit Roots

1-minute realized volatility	**5-minute realized volatility**	**Range-based volatility**	**Algorithmic trading**
-1.8919**	-2.0354**	-7.8771***	-3.917***

Note: *, ** and *** Denote Significance at the 10%, 5% and 1%.

Appendix A-8 Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Proxies for Each Stock Using Ordinary Least Square Estimation Method

Stock	AT_I	AT_F	AT_I x AT_F	AT_I	AT_F	AT_I x AT_F
AAV	-0.0002*	-0.0001	$-2.2x10^{-6}$	-0.0006**	-0.0011**	$-7.0x10^{-6}$**
	(-1.893)	(-0.599)	(-1.566)	(-2.282)	(-2.229)	(-2.287)
ADVANC	-0.0001**	-0.0003***	$-9.5x10^{-7}$***	-0.0004***	-0.0010***	$-3.5x10^{-6}$***
	(-2.374)	(-2.755)	(-2.870)	(-2.886)	(-3.556)	(-3.709)
AMATA	0.0005**	0.0012	$1.5x10^{-5}$	0.0003	0.0001	$6.3x10^{-6}$
	(2.441)	(1.508)	(1.186)	(0.857)	(0.120)	(0.334)
ANAN	0.0001	0.0005	$1.6 x10^{-5}$**	$8.3 x10^{-5}$	0.0008	$3.3 x10^{-5}$**
	(0.747)	(1.515)	(2.135)	(0.247)	(1.221)	(2.052)
AOT	$-2.4x10^{-5}$	$-7.1x10^{-6}$	$-9.4x10^{-8}$	$-4.1x10^{-5}$	-0.0002	$-5.7x10^{-7}$
	(-0.691)	(-0.109)	(-0.438)	(-0.587)	(-1.174)	(-1.313)
AP	$-8.4x10^{-6}$	-0.0005	$-6.8x10^{-6}$	-0.0002	-0.0003	$2.2x10^{-6}$
	(-0.052)	(-0.905)	(-1.283)	(-0.496)	(-0.152)	(0.137)
BA	-0.0001	-0.0003*	$-9.6x10^{-7}$	$-9.7x10^{-5}$	-0.0004	$-3.8x10^{-6}$
	(-1.410)	(-1.745)	(-0.959)	(-0.710)	(-1.449)	(-2.056)
BANPU	$-5.7x10^{-5}$	-0.0003**	$-1.0x10^{-6}$**	$6.7x10^{-5}$	$5.2x10^{-6}$	$-9.9x10^{-7}$
	(-1.027)	(-2.377)	(-2.259)	(0.580)	(0.019)	(-1.076)
BBL	$-3.1x10^{-5}$	$-2.7x10^{-5}$	$-6.1x10^{-7}$**	$1.7x10^{-5}$	$-2.9x10^{-5}$	$-7.7x10^{-7}$
	(-0.939)	(-0.592)	(-2.588)	(0.233)	(-0.295))	(-1.474)
BCP	-0.0001	-0.0005	$-6.2x10^{-6}$**	-0.0003*	-0.0015***	$-7.2x10^{-6}$**
	(-0.901)	(-1.271)	(-2.577)	(-1.718)	(-2.792)	(-2.134)
BDMS	$2.6x10^{-5}$	$1.9x10^{-5}$	$-5.0x10^{-8}$	0.0001	0.0003*	$-1.1x10^{-7}$
	(0.532)	(0.215)	(-0.085)	(1.274)	(1.820)	(-0.107)
BEAUTY	$-8.1x10^{-5}$	0.0004	$-3.2x10^{-6}$	$3.2x10^{-5}$	0.0007	$-4.4x10^{-6}$
	(-0.558)	(1.315)	(-0.938)	(0.119)	(1.181)	(-0.709)
BEC	0.0001	0.0032**	$2.7x10^{-6}$	0.0001	0.0044	$1.3x10^{-5}$
	(0.174)	(2.235)	(0.063)	(0.122)	(1.566)	(0.149)
BEM	$-9.6x10^{-5}$	$9.2x10^{-5}$	$-1.3x10^{-6}$	-0.0002*	0.0002	$-3.6x10^{-6}$**
	(-1.382)	(0.437)	(-1.394)	(-1.749)	(0.448)	(-2.205)
BH	$4.9x10^{-5}$	0.0007**	$1.7x10^{-6}$	$-8.6x10^{-5}$	0.0009	$-2.9x10^{-7}$
	(0.463)	(2.595)	(0.853)	(-0.377)	(1.567)	(-0.068)
BJCHI	0.0002	$5.2x10^{-5}$	$-3.1x10^{-5}$	-0.0009	-0.0025	-0.0001
	(0.625)	(0.050)	(-0.679)	(-1.097)	(-1.152)	(-1.211)

Appendix A-8 (Continued)

Stock	AT_I	AT_F	AT_I x AT_F	AT_I	AT_F	AT_I x AT_F
BLA	$9.6x10^{-5}$	0.0002	$-5.6x10^{-5}$	$1.5x10^{-5}$	-0.0002	$-9.6x10^{-6}$
	(0.563)	(0.552)	(-1.427)	(0.051)	(-0.308)	(-1.443)
BLAND	-0.0003^{**}	-0.0001	$-6.1x10^{-6}$	-0.0005^{**}	-0.0004	$-1.5x10^{-5}$
	(-2.369)	(-0.245)	(-1.326)	(-2.522)	(-0.605)	(-2.129)
BTS	$-1.7x10^{-5}$	-0.0005^{*}	$-4.9x10^{-6**}$	-0.0004^{**}	-0.0013^{***}	$-1.4x10^{-5***}$
	(-0.153)	(-1.905)	(-2.318)	(-2.012)	(-2.012)	(-3.616)
CBG	$-3.0x10^{-5}$	$9.0x10^{-5}$	$-1.9x10^{-6}$	$-3.4x10^{-5}$	0.0002	$-6.7x10^{-6}$
	(-0.375)	(0.288)	(-1.020)	(-0.190)	(0.263)	(-1.643)
CENTEL	$2.5x10^{-5}$	0.0006	$-5.0x10^{-6}$	-0.0003	-0.0002	$-1.1x10^{-5}$
	(0.137)	(1.235)	(-0.877)	(-0.734)	(-0.257)	(-1.010)
CHG	-0.0001	0.0001	$-7.7x10^{-6}$	-0.0002	0.0004	$-2.6x10^{-6}$
	(-0.628)	(0.205)	(-1.003)	(-0.828)	(0.415)	(-0.229)
CK	-0.0004^{***}	-0.0007^{***}	$-4.4x10^{-6***}$	-0.0007***	-0.0011***	$-7.5x10^{-6***}$
	(-3.937)	(-4.239)	(-3.948)	(-3.542)	(-3.853)	(-3.859)
CKP	$-3.9x10^{-5}$	-0.0012^{***}	$-1.6x10^{-5***}$	-0.0002	-0.0022^{***}	$-2.4x10^{-5***}$
	(-0.280)	(-3.102)	(-4.729)	(-0.793)	(-2.726)	(-3.498)
CPALL	$3.2x10^{-7}$	$-4.6x10^{-6}$	$-2.1x10^{-7}$	$1.9x10^{-5}$	$7.7x10^{-5}$	$-1.4x10^{-7}$
	(0.008)	(-0.047)	(-0.736)	(0.235)	(0.406)	(-0.264)
CPF	$1.2x10^{-5}$	$-8.9x10^{-5}$	$4.8x10^{-7}$	$-3.7x10^{-6}$	$4.4x10^{-5}$	$5.2x10^{-8}$
	(0.101)	(-0.366)	(0.438)	(-0.022)	(0.128)	(0.034)
CPN	0.0001^{*}	0.0006^{***}	$5.8x10^{-7}$	0.0001	0.0009^{***}	$5.9x10^{-7}$
	(1.658)	(4.240)	(0.639)	(0.781)	(3.190)	(0.304)
DELTA	0.0002	0.0014^{***}	$1.1x10^{-5}$	$6.7x10^{-5}$	0.0021^{*}	$7.8x10^{-6}$
	(1.029)	(3.010)	(1.339)	(0.122)	(1.876)	(0.372)
DTAC	-0.0002^{**}	-0.0003^{*}	$-3.8x10\text{-}6^{***}$	-0.0004^{**}	-0.0009^{***}	$-6.4x10^{-6***}$
	(-1.987)	(-1.748)	(-3.407)	(-2.526)	(-3.263)	(-3.390)
EGCO	$2.3x10^{-5}$	0.0005^{*}	$1.1x10^{-6}$	$3.0x10^{-5}$	0.0011	$3.2x10^{-6}$
	(0.264)	(1.923)	(0.476)	(0.114)	(1.375)	(0.461)
EPG	$1.1x10^{-5}$	-0.0003	$-4.5x10^{-6*}$	-0.0002	$-2.7x10^{-5}$	$-8.7x10^{-6*}$
	(0.141)	(-0.989)	(-1.790)	(-1.152)	(-0.048)	(-1.684)
GL	-0.0004^{***}	-0.0008^{***}	$-1.5x10^{-5***}$	-0.0003	-0.0003	$-1.4x10^{-5*}$
	(-3.321)	(-2.787)	(-4.092)	(-1.237)	(-0.479)	(-1.678)
GLOW	0.0002^{*}	0.0005	$-6.2x10^{-6}$	0.0003	0.0004	$-2.7x10^{-5**}$
	(1.951)	(1.490)	(-1.234)	(0.802)	(0.453)	(-2.018)

Appendix A-8 (Continued)

Stock	AT_I	AT_F	AT_I x AT_F	AT_I	AT_F	AT_I x AT_F
GPSC	-5.1×10^{-6}	4.9×10^{-5}	-3.2×10^{-7}	-9.1×10^{-5}	7.3×10^{-6}	-5.7×10^{-7}
	(-0.075)	(0.169)	(-0.251)	(-0.791)	(0.015)	(-0.268)
GUNKUL	2.4×10^{-5}	0.0006^{*}	3.7×10^{-6}	-0.0003	0.0004	5.8×10^{-6}
	(0.102)	(1.791)	(0.743)	(-0.677)	(0.738)	(0.708)
HANA	0.0011^{***}	0.0023^{***}	5.7×10^{-6}	0.0012^{**}	0.0014	-3.0×10^{-5}
	(3.605)	(3.225)	(0.334)	(2.517)	(1.236)	(-1.115)
HMPRO	-0.0005	-0.0007	-1.1×10^{-5}	2.3×10^{-5}	0.0008	1.0×10^{-5}
	(-1.616)	(-0.933)	(-1.251)	(0.046)	(0.601)	(0.672)
ICHI	0.0001	-0.0001	-9.8×10^{-6}	0.0002	-0.0007	-1.1×10^{-5}
	(0.455)	(-0.116)	(-0.822)	(0.711)	(-0.621)	(-0.703)
INTUCH	-5.6×10^{-5}	-2.4×10^{-5}	$-9.8 \times 10^{-7**}$	-8.9×10^{-5}	3.2×10^{-5}	$-1.7 \times 10^{-6**}$
	(-1.098)	(-0.259)	(-2.390)	(-0.852)	(0.169)	(-2.052)
IRPC	-8.7×10^{-5}	-5.9×10^{-5}	5.3×10^{-7}	-0.0002	-0.0006	-4.3×10^{-6}
	(-0.685)	(-0.160)	(0.199)	(-0.909)	(-1.169)	(-1.107)
ITD	-0.0002^{*}	-0.0015^{***}	$-1.2\text{x}10\text{-}5^{***}$	-0.0004^{*}	-0.0035^{***}	$-2.6 \times 10^{-5***}$
	(-1.907)	(-3.603)	(-5.098)	(-1.835)	(-4.718)	(-6.094)
KBANK	2.3×10^{-5}	2.0×10^{-5}	-6.8×10^{-8}	6.0×10^{-5}	7.9×10^{-5}	1.3×10^{-8}
	(0.606)	(0.328)	(-0.342)	(0.633)	(0.506)	(0.026)
KCE	9.9×10^{-5}	0.0006^{***}	$-1.6 \times 10^{-6***}$	8.4×10^{-5}	0.0012^{***}	$-3.6 \times 10^{-6***}$
	(1.494)	(3.715)	(-5.827)	(0.504)	(3.023)	(-5.357)
KKP	-3.3×10^{-5}	0.0002	$-4.1 \times 10^{-6**}$	-3.4×10^{-5}	0.0006	-3.9×10^{-6}
	(-0.394)	(0.686)	(-2.033)	(-0.209)	(1.187)	(-1.013)
KTB	-1.9×10^{-5}	4.4×10^{-5}	-4.9×10^{-7}	0.0001	-7.3×10^{-5}	-9.4×10^{-8}
	(-0.292)	(0.339)	(-0.820)	(1.093)	(-0.379)	(-0.107)
KTC	0.0005^{***}	0.0012^{***}	$2.0 \times 10^{-5***}$	0.0013^{***}	0.0032^{***}	$5.1 \times 10^{-5***}$
	(3.551)	(3.035)	(3.471)	(3.856)	(3.385)	(3.796)
LH	8.7×10^{-5}	0.0001	-3.0×10^{-6}	0.0004	0.0008	-3.1×10^{-6}
	(0.565)	(0.372)	(-1.175)	(1.415)	(1.233)	(-0.634)
LHBANK	0.0001	0.0006^{**}	-6.8×10^{-7}	-4.3×10^{-6}	0.0001	-3.8×10^{-6}
	(1.128)	(2.271)	(-0.293)	(-0.031)	(0.252)	(-1.141)
LPN	9.7×10^{-5}	-0.0002	-2.0×10^{-6}	-9.2×10^{-5}	-1.7×10^{-6}	-6.0×10^{-6}
	(0.609)	(-0.364)	(-0.266)	(-0.364)	(-0.002)	(-0.504)
MAJOR	0.0005^{***}	0.0016^{***}	2.5×10^{-6}	0.0006^{**}	0.0022^{***}	5.4×10^{-6}
	(3.786)	(4.680)	(0.710)	(2.518)	(4.114)	(0.958)

Appendix A-8 (Continued)

Stock	AT_I	AT_F	AT_I x AT_F	AT_I	AT_F	AT_I x AT_F
MINT	0.0005	0.0009**	5.5×10^{-7}	0.0002	0.0014**	2.2×10^{-6}
	(1.560)	(2.515)	(0.246)	(0.802)	(1.988)	(0.486)
PLANB	-2.7×10^{-5}	-0.0006	-8.0×10^{-6}	-0.0002	-0.0009	-8.6×10^{-6}
	(-0.163)	(-1.068)	(-1.100)	(-0.763)	(-0.828)	(-0.677)
PS	1.1×10^{-5}	5.1×10^{-5}	5.2×10^{-7}	-0.0003	-0.0009	-1.9×10^{-6}
	(0.050)	(0.089)	(0.074)	(-1.086)	(-1.104)	(-0.189)
PTG	-3.7×10^{-5}	5.4×10^{-4}	1.2×10^{-6}	0.0003	0.0013	5.7×10^{-6}
	(-0.298)	(1.077)	(0.330)	(0.964)	(1.203)	(0.703)
PTT	-2.0×10^{-5}	6.9×10^{-5}	-1.3×10^{-7}	-1.9×10^{-5}	0.0002*	-2.5×10^{-7}
	(-0.798)	(1.472)	(-1.108)	(-0.291)	(1.659)	(-0.855)
PTTEP	-4.3×10^{-5}	-6.5×10^{-5}	-6.1×10^{-7}	-6.4×10^{-5}	-6.9×10^{-5}	-1.5×10^{-6}
	(-0.990)	(-0.572)	(-1.382)	(-0.584)	(-0.239)	(-1.307)
PTTGC	-5.4×10^{-5}	-5.0×10^{-6}	-7.8×10^{-7}	-5.9×10^{-5}	2.7×10^{-5}	-1.5×10^{-6}
	(-0.775)	(-0.031)	(-0.860)	(-0.360)	(0.070)	(-0.692)
QH	-8.4×10^{-5}	0.0007	-7.2×10^{-6}	-0.0003	0.0003	-1.5×10^{-5}
	(-0.344)	(1.077)	(-0.662)	(-1.021)	(0.366)	(-1.073)
ROBINS	3.0×10^{-5}	0.0011**	-1.9×10^{-6}	-0.0003	0.0016	-1.1×10^{-5}
	(0.236)	(2.186)	(-0.345)	(-0.862)	(1.323)	(-0.803)
RS	0.0002	-0.0005	-1.0×10^{-5}	0.0004	8.4×10^{-5}	1.3×10^{-6}
	(1.050)	(-0.461)	(-0.617)	(1.149)	(0.044)	(0.045)
S	-0.0003*	-0.0001	-1.1×10^{-5}**	-0.0009*	-0.0012	-2.2×10^{-5}*
	(-1.865)	(-0.462)	(-2.133)	(-1.842)	(-1.553)	(-1.756)
SAMART	-0.0003**	-4.4×10^{-5}	-1.1×10^{-5}**	-0.0006**	-0.0012	-2.7×10^{-5}***
	(-2.250)	(-0.072)	(-2.084)	(-2.384)	(-1.085)	(-2.889)
SAWAD	0.0001	2.0×10^{-5}	-2.2×10^{-6}	0.0004	0.0001	-1.2×10^{-6}
	(0.533)	(0.062)	(-0.691)	(0.919)	(0.194)	(-0.161)
SCB	1.8×10^{-5}	8.7×10^{-6}	-3.0×10^{-7}	-0.0001	-0.0002	-1.6×10^{-6}***
	(0.583)	(0.136)	(1.346)	(-1.586)	(-1.495)	(-3.013)
SCC	-4.1×10^{-5}	1.5×10^{-5}	-4.7×10^{-7}**	-0.0001	5.9×10^{-5}	-9.2×10^{-7}*
	(-1.121)	(0.206)	(-2.085)	(-1.303)	(0.319)	(-1.664)
SGP	-0.0002	0.0009	-9.4×10^{-6}	-0.0004*	0.0003	-1.8×10^{-5}*
	(-1.184)	(1.500)	(-1.327)	(-1.737)	(0.279)	(-1.752)
SIRI	-0.0003	-0.0013**	-1.7×10^{-5}*	-0.0004	-0.0018**	-2.2×10^{-5}
	(-1.118)	(-2.290)	(-1.900)	(-0.977)	(-2.051)	(-1.553)

Appendix A-8 (Continued)

Stock	AT_I	AT_F	AT_I x AT_F	AT_I	AT_F	AT_I x AT_F
SPALI	$9.8x10^{-5}$	$-9.0x10^{-5}$	$-7.1x10^{-6**}$	$-4.3x10^{-5}$	-0.0007	$-2.0x10^{-5***}$
	(1.155)	(-0.302)	(-2.138)	(-0.303)	(-1.293)	(-3.645)
SPCG	$4.6x10^{-6}$	0.0007	$-2.7x10^{-5}$	-0.0003	0.0015	$-2.2x10^{-5}$
	(0.019)	(1.100)	(-1.289)	(-0.714)	(1.575)	(-0.719)
STEC	-0.0003^{***}	-0.0006^{***}	$-2.9x10^{-6}$	-0.0004^{**}	-0.0010^{***}	$-5.1x10^{-6**}$
	(-3.559)	(-3.237)	(-2.505)	(-2.260)	(-3.187)	(-2.357)
STPI	-0.0007^{***}	-0.0012^{***}	$-3.2x10^{-5***}$	-0.0016^{***}	-0.0022^{**}	$-6.0x10^{-5***}$
	(-4.199)	(-3.333)	(-5.797)	(-3.252)	(-2.243)	(-4.010)
SVI	0.0004^{*}	0.0008^{***}	$7.3x10^{-6}$	0.0002	0.0013^{**}	$1.9x10^{-5}$
	(1.833)	(2.768)	(0.962)	(0.531)	(2.448)	(1.323)
TASCO	-0.0005^{**}	-0.0007^{**}	$-7.8x10^{-6**}$	-0.0004	-0.0009	$-1.1x10^{-5*}$
	(-2.076)	(-2.377)	(-2.465)	(-1.108)	(-1.500)	(-1.947)
TCAP	0.0001	0.0004	$-7.8x10^{-7}$	0.0001	0.0005	$-1.4x10^{-7}$
	(0.984)	(1.480)	(-0.487)	(0.881)	(1.194)	(-0.064)
THAI	-0.0003^{**}	-0.0004	$-1.3x10^{-6}$	-0.0003	-0.0005	$-2.2x10^{-7}$
	(-2.455)	(-1.542)	(-1.298)	(-1.168)	(-0.822)	(-0.099)
THCOM	-0.0001	0.0004	$4.4x10^{-7}$	-0.0001	0.0001	$-9.7x10^{-6}$
	(-1.157)	(0.969)	(0.079)	(-0.441)	(0.138)	(-0.745)
TISCO	$-2.2x10^{-5}$	0.0003	$-1.7x10^{-6}$	$-8.5x10^{-5}$	0.0005^{*}	$-1.5x10^{-6}$
	(-0.244)	(1.638)	(-1.555)	(-0.550)	(1.884)	(-0.783)
TMB	-0.0001	-0.0003	$-3.0x10^{-6}$	-0.0002	-0.0006	$-6.6x10^{-6}$
	(-0.848)	(-0.796)	(-1.029)	(-0.783)	(-1.192)	(-1.640)
TOP	$4.8x10^{-6}$	-0.0001	$-1.8x10^{-6}$	$2.5x10^{-7}$	-0.0005	$-5.6x10^{-6*}$
	(0.068)	(-0.546)	(-1.280)	(0.001)	(-0.991)	(-1.694)
TPIPL	-0.0005^{***}	-0.0008^{***}	$-5.8x10^{-6***}$	-0.0010^{***}	-0.0014^{***}	$-9.2x10^{-6***}$
	(-3.865)	(-4.014)	(-4.206)	(-4.440)	(-4.288)	(-4.157)
TRUE	-0.0002^{***}	-0.0003^{**}	$-2.2x10^{-6***}$	-0.0004^{***}	-0.0006^{**}	$-4.2x10^{-6***}$
	(-3.318)	(-2.598)	(-3.552)	(-2.882)	(-2.376)	(-3.749)
TTCL	-0.0005^{***}	-0.0010^{**}	$-1.8x10\text{-}5^{***}$	-0.0010^{***}	-0.0023^{**}	$-3.7x10^{-5***}$
	(-3.344)	(-2.358)	(-3.147)	(-3.276)	(-2.556)	(-3.059)
TTW	0.0008^{*}	0.0036^{***}	$3.6x10^{-5}$	0.0004	0.0013	$2.6x10^{-5}$
	(1.937)	(2.744)	(1.212)	(0.747)	(0.718)	(0.659)
TU	0.0001	0.0003	$1.3x10^{-6}$	0.0004^{**}	0.0013^{**}	$7.5x10^{-6}$
	(1.080)	(0.929)	(0.451)	(2.569)	(2.364)	(1.567)

Appendix A-8 (Continued)

Stock	AT_I	AT_F	AT_I x AT_F	AT_I	AT_F	AT_I x AT_F
UNIQ	4.2x10^{-5}	-0.0005**	-6.8x10^{-6***}	-2.0x10^{-5}	-0.0013**	-1.5x10^{-5***}
	(0.507)	(-2.218)	(-3.122)	(-0.104)	(-2.455)	(-3.077)
VGI	2.3x10^{-5}	-0.0020	-3.4x10^{-5**}	-0.0004	-0.0042***	-4.2x10^{-5***}
	(0.057)	(-1.430)	(-2.159)	(-0.932)	(-2.963)	(-2.699)
VNG	0.0003**	0.0001	-2.6x10^{-6}	0.0007***	0.0014	4.8x10^{-6}
	(2.133)	(0.186)	(-0.297)	(3.032)	(0.987)	(0.309)
WHA	-1.3x10^{-5}	-0.0003	-5.6x10^{-6**}	-0.0001	-0.0002	-5.3x10^{-6}
	(-0.115)	(-1.176)	(-2.341)	(-0.600)	(-0.356)	(-1.038)
WORK	4.2x10^{-6}	-0.0001	-4.2x10^{-6}	-6.4x10^{-5}	-0.0007*	-1.3x10^{-5**}
	(0.038)	(-0.563)	(-1.573)	(-0.292)	(-1.806)	(-2.463)

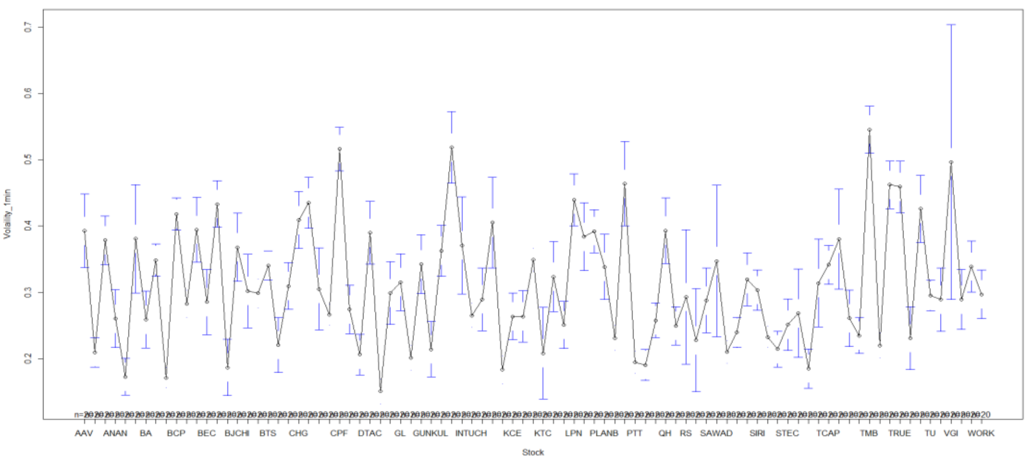
Appendix A-9 Multicollinearity Problem during the Volatile Period

The variance inflation factor (VIF) is computed to detect the multicollinearity. As all the scores of the VIF is lower than five, there is no evidence that there is multicollinearity in the variables.

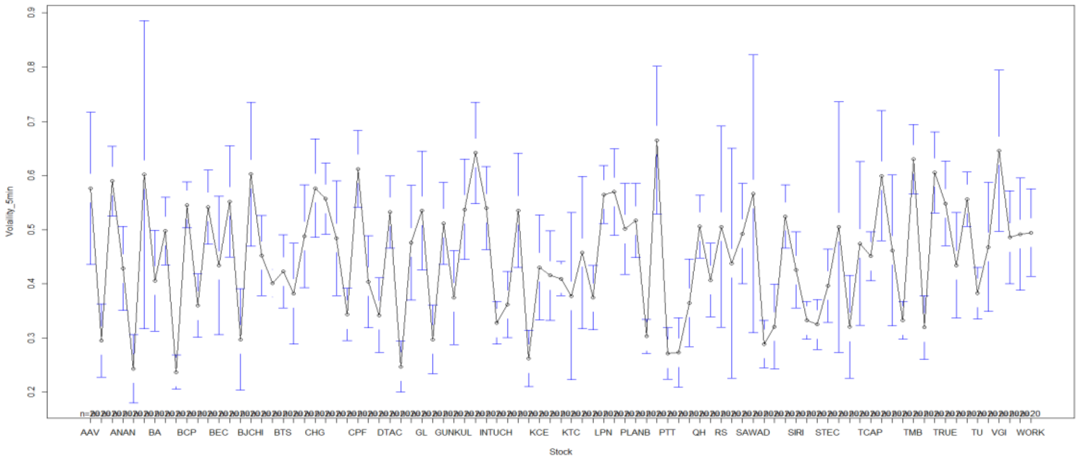
Algorithmic Trading	Price-to-book Ratio	Share Turnover	Inverse of Price	Effective Half Spread	Natural Log of Market Cap
3.0269	1.0225	1.4465	0.2092	1.1483	2.5999

Appendix A-10 Heterogeneity in the Volatility data during the Volatile Period

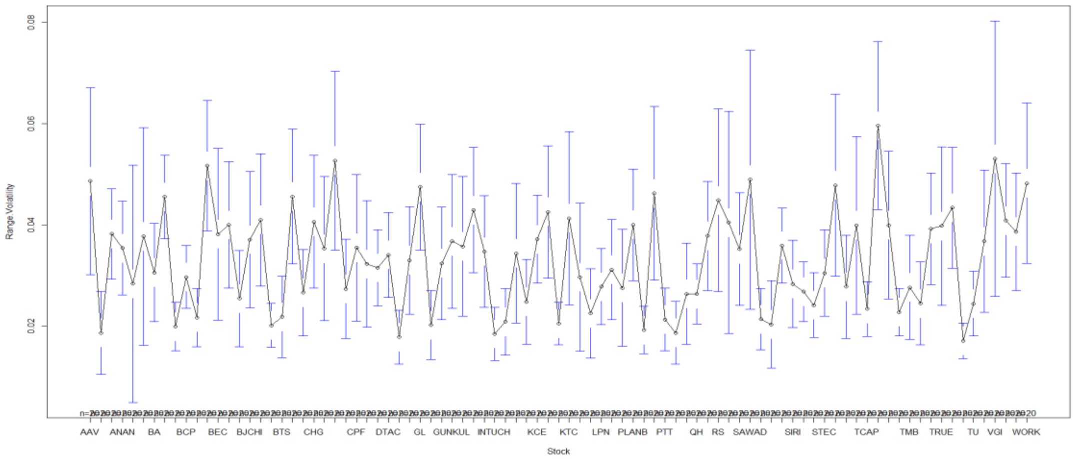
The mean plot of the one-minute realized volatility across individual



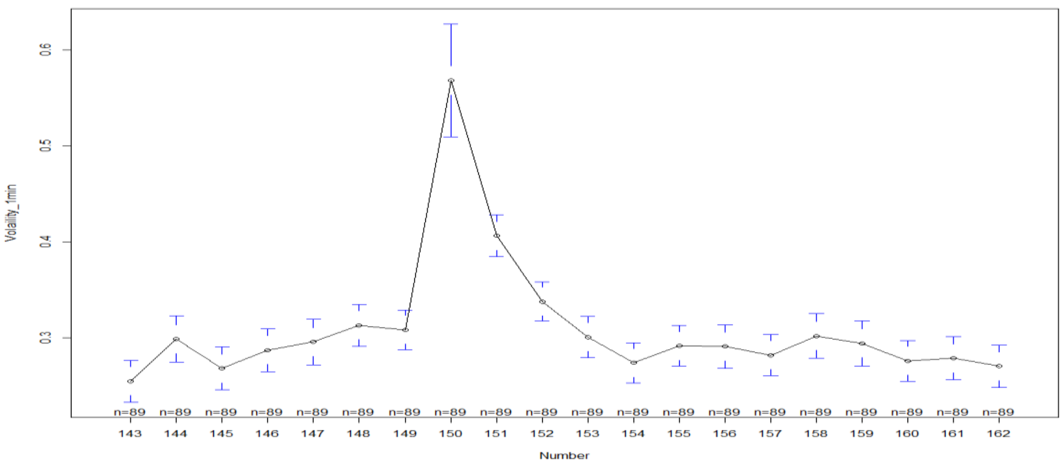
The mean plot of the five-minute realized volatility across individual



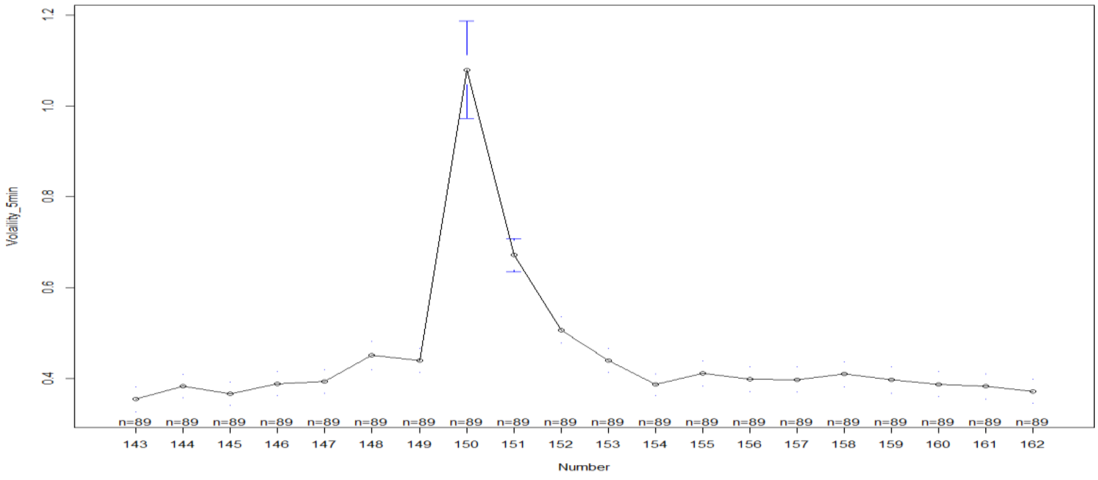
The mean plot of the range-based realized volatility across individual



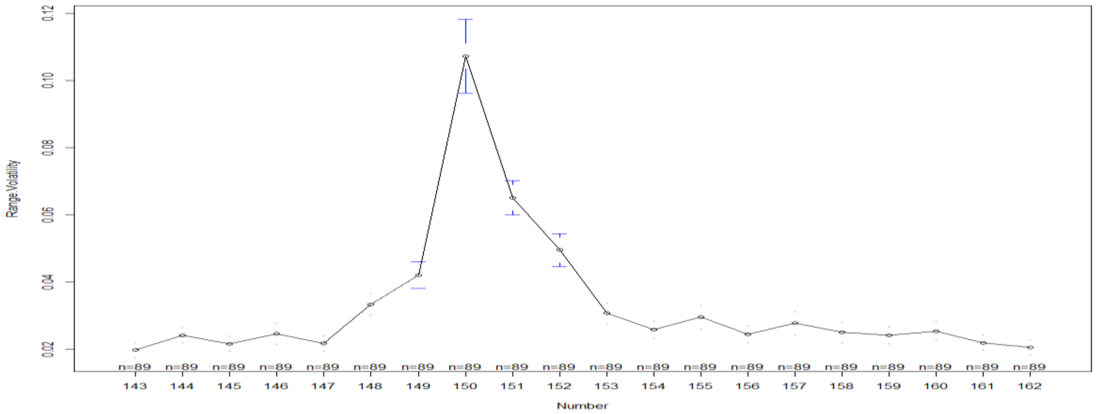
The mean plot of the one-minute realized volatility across time



The mean plot of the five-minute realized volatility across time



The mean plot of the range-based volatility across time



Appendix A-11 Restricted F-Tests during the Volatile Period

The restricted F-test for the two-way effects are displayed below, confirming that the two-way fixed-effect model is a better choice than the pooled OLS model.

	Model 1 **1-minute realized volatility**	**Model 2** **5-minute realized volatility**	**Model 3** **Range-based volatility**
F-statistics	16.597	24.450	26.265
p-value	< 0.01	< 0.01	< 0.01

Appendix A-12 Chi-square Statistics for Individual and Time Effects during the Volatile Period

	Model 1	**Model 2**	**Model 3**
F-statistics	69.680	11.036	26.560
p-value	< 0.01	0.05	< 0.01

Appendix A-13 Regression Coefficients during the Volatile Period

Pooled OLS Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Volatility Measures during the Volatile Period.

Variable	**Model 1** **1-minute realized volatility**	**Model 2** **5-minute realized volatility**	**Model 3** **Range-based volatility**
Intercept	0.0028	0.6505^{***}	0.0886^{***}
	(0.064)	(7.078)	(7.973)
AT_{it}	5.1981×10^{-5}	-2.4801×10^{-4}	$-6.4582 \times 10^{-5**}$
	(0.507)	(-1.161)	(-2.500)
Price-to-book ratio	0.0029^{***}	0.0040^{***}	0.0008^{***}
	(4.908)	(3.238)	(5.682)
Share turnover	7.6964^{***}	13.3648^{***}	1.8991^{***}
	(18.026)	(15.019)	(17.650)

Appendix A-13 (Continued)

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
The inverse of price	0.0460***	-0.0241	-0.0066
	(2.619)	(-0.658)	(-1.494)
Effective half spread	0.7338***	0.7488***	0.0073
	(37.833)	(18.523)	(1.500)
Natural log of market cap	0.0044	-0.0339***	-0.0050***
	(1.363)	(-5.042)	(-6.157)
Adjusted R^2	53.05%	30.32%	25.39%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Two-way Random-Effects Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Volatility Measures during the Volatile Period.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
Intercept	0.0830	0.7114***	0.0856***
	(1.358)	(7.043)	(6.564)
Algorithmic Trading	2.0291×10^{-5}	-9.0996×10^{-5}	-3.8095×10^{-5}*
	(0.194)	(-0.488)	(-1.663)
Price-to-book ratio	0.0029***	0.0045***	0.0008***
	(2.991)	(2.884)	(4.022)
Share turnover	4.6295***	7.5988***	1.4396***
	(10.213)	(9.424)	(14.508)
The inverse of price	0.0629**	-0.0221	-0.0079
	(2.193)	(-0.484)	(-1.312)

Appendix A-13 (Continued)

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
Effective half spread	0.6495*** (32.248)	0.6753*** (18.915)	0.0101** (2.301)
Natural log of market cap	0.0012 (0.273)	-0.0345*** (-4.834)	-0.0046*** (-4.995)
Adjusted R^2	40.68%	23.39%	16.46%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Appendix A-14 Choi (2001)'s z Statistics for Panel Unit Roots during the Volatile Period

1-minute realized volatility	5-minute realized volatility	Range-based volatility	Algorithmic trading
-22.043***	-21.026***	-17.667***	-27.768***

Note: *, ** and *** Denote Significance at the 10%, 5% and 1%.

Appendix A-15 Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors during the Volatile Period

Pooled OLS Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables on Volatility Measures during the Volatile Period.

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
Intercept	0.0675 (1.349)	0.6623*** (6.328)	0.0684*** (5.416)

Appendix A-15 (Continued)

Variable	Model 1 1-minute realized volatility	Model 2 5-minute realized volatility	Model 3 Range-based volatility
AT_I_{it}	$-5.9640x10^{-5}$	$-2.7694x10^{-5}$	$2.9421x10^{-5**}$
	(-1.135)	(-0.252)	(2.217)
AT_F_{it}	$-2.6042x10^{-4**}$	$-1.7632x10^{-4}$	$4.8062x10^{-5*}$
	(-2.268)	(-0.734)	(1.657)
$AT\_I_{it}xAT\_F_{it}$	$-8.7956x10^{-7**}$	$-1.6815x10^{-7}$	$3.1077x10^{-7***}$
	(-2.400)	(-0.219)	(3.358)
Price-to-book ratio	0.0030^{***}	0.0042^{***}	0.0009^{***}
	(5.002)	(3.339)	(5.731)
Share turnover	7.1962^{***}	13.4325^{***}	2.1006^{***}
	(16.127)	(14.388)	(18.637)
The inverse of price	0.0463^{***}	-0.0313	-0.0089**
	(2.629)	(-0.849)	(-1.996)
Effective half	0.7387^{***}	0.7447^{***}	0.0050
spread	(38.365)	(18.488)	(1.034)
Natural log of	-0.0009	-0.0345^{***}	-0.0032^{***}
market cap	(-0.242)	(-4.478)	(3.469)
Adjusted R^2	53.24%	30.29%	25.60%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1%.

APPENDIX B

THE IMPACT OF ALGORITHMIC TRADING ON LIQUIDITY

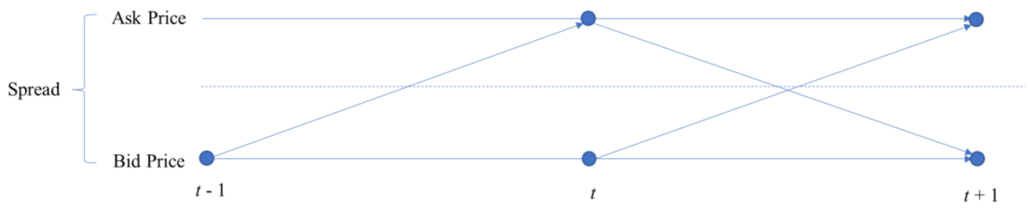
APPENDIX B

THE IMPACT OF ALGORITHMIC TRADING ON LIQUIDITY

Appendix B-1 Roll's Effective Bid-ask Spread

Roll (1984) developed a measure of the effective bid-ask spread from a time-series of prices. The assumption is that the securities are traded in efficient market and therefore, the prices reflect all publicly available information. Hence, the prices move randomly. Thus, the change in price will happen only when there is new information available. A market maker is compensated to supply liquidity with bid-ask spread. The average between bid-ask price is the new equilibrium price. As negative serial dependence in price changes is due to the activities of market maker, the bid-ask spread can be measured as a negative serial dependence.

The change in Price Path



Assuming that the probability of price reversal is equal to one-half, the covariance between successive price changes (Δp_t) can be expressed as:

$$Cov(\Delta p_t, \Delta p_{t+1}) = \frac{1}{8}(-s^2 - s^2) = -s^2/4$$

where s is effective half bid-ask spread and p is the transaction price.

Appendix B-2 Variance Inflation Factor

Daily Variables

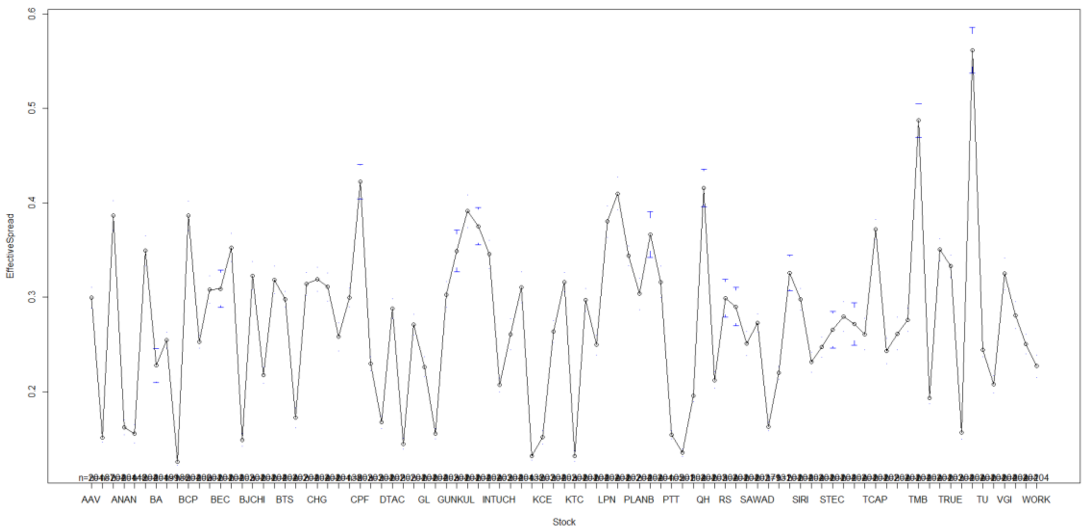
Algorithmic Trading	Realized Volatility	Share Turnover	Inverse of Price	Natural Log of Market Cap
2.8250	1.2141	1.6398	1.1545	2.5446

Monthly Variables

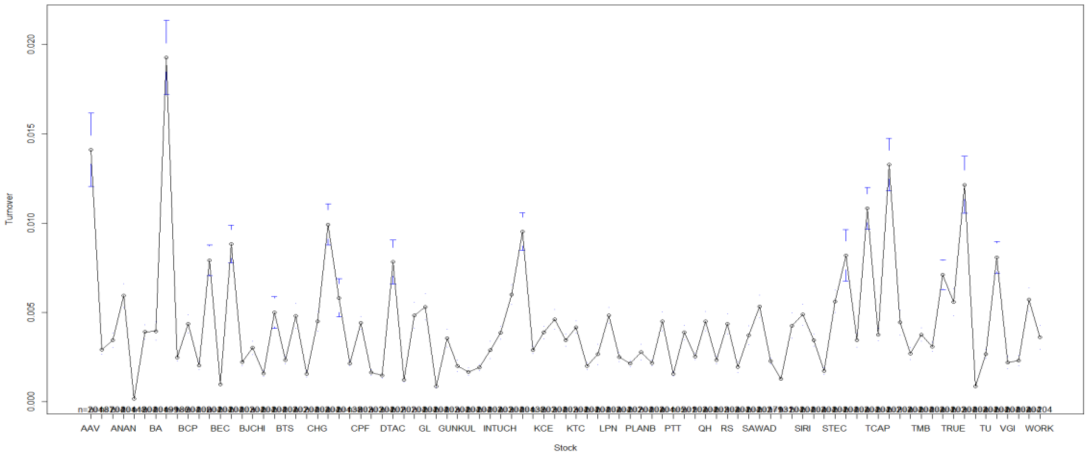
Algorithmic Trading	Realized Volatility	Inverse of Price	Natural Log of Market Cap
2.5769	1.1014	1.1539	2.7154

Appendix B-3 Heterogeneity Across Individuals and Time

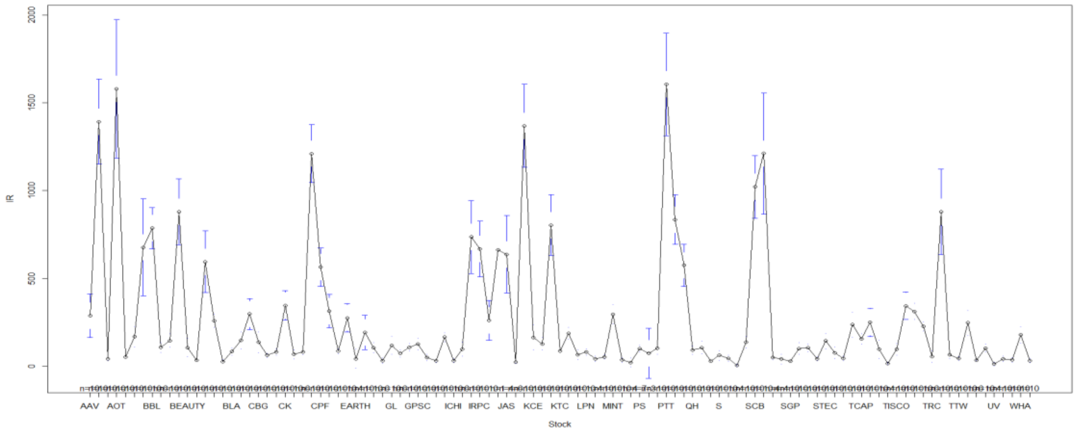
The mean plot of the effective spread across individual



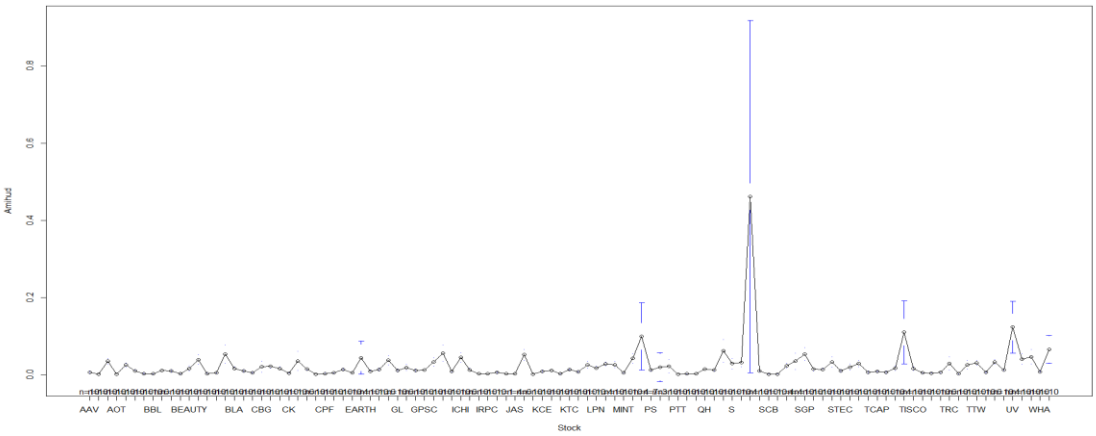
The mean plot of the share turnover across individual



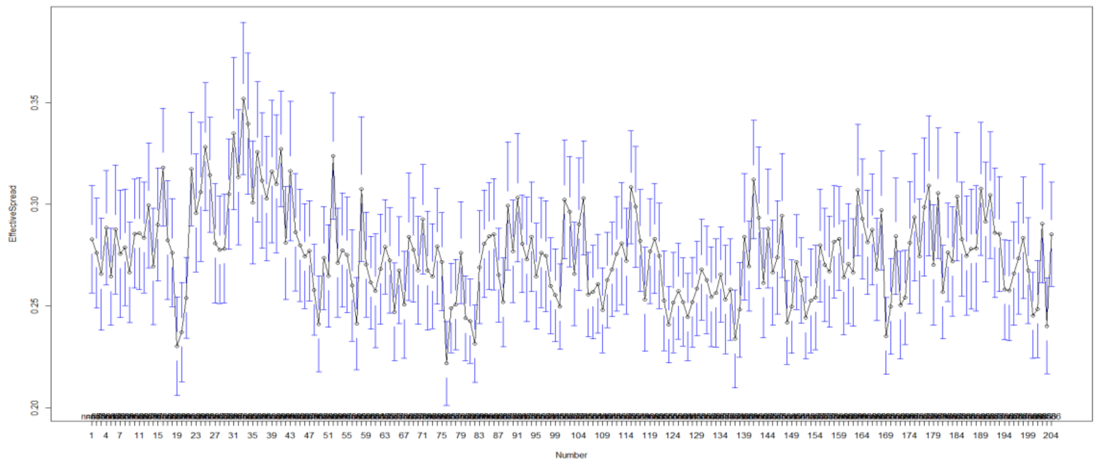
The mean plot of the liquidity ratio across individual



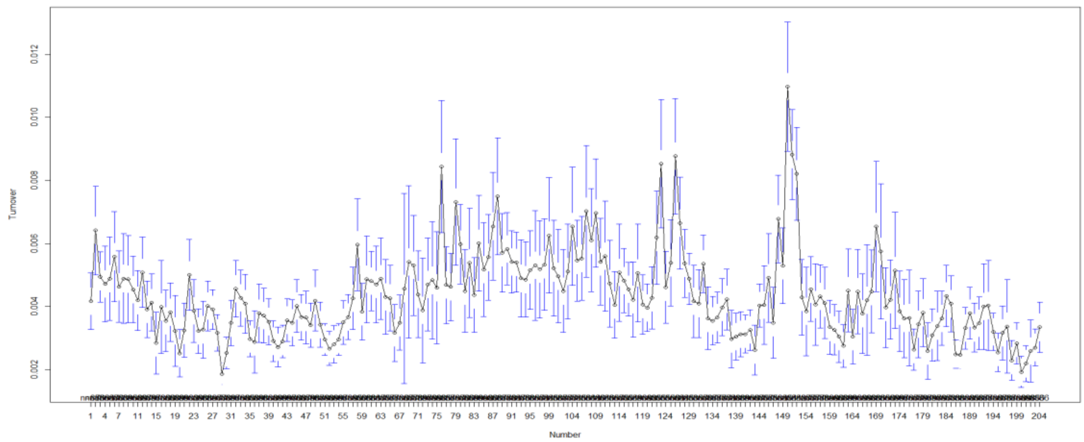
The mean plot of the Amihud's illiquidity ratio across individual



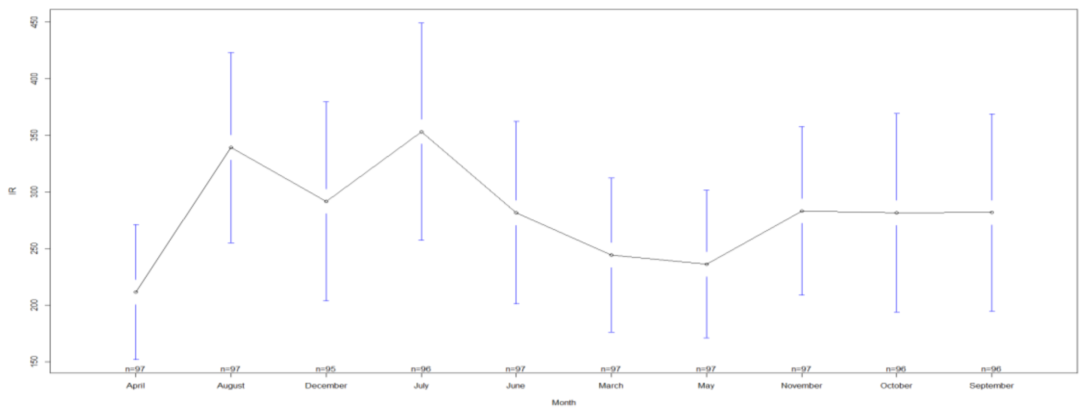
The mean plot of the effective spread across time



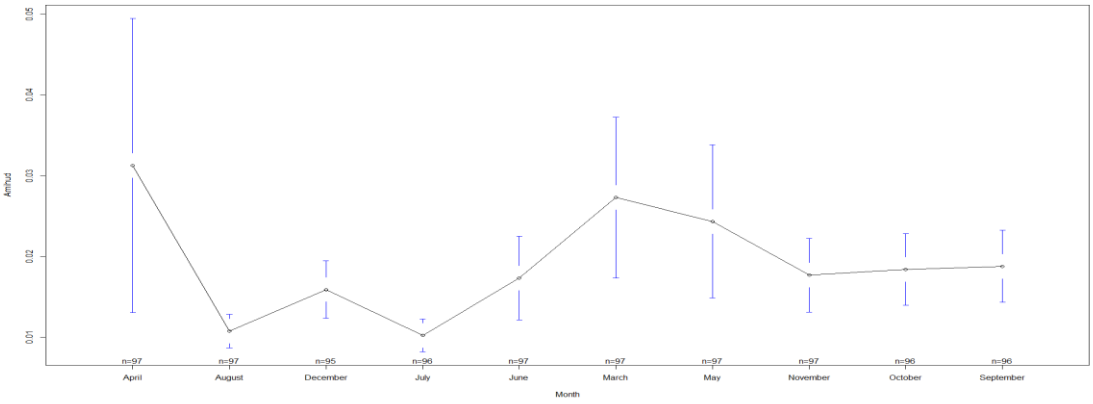
The mean plot of the share turnover across time



The mean plot of the liquidity ratio across time



The mean plot of the Amihud's illiquidity estimate across time



Appendix B-4 Restricted F-Test

Restricted F-Test for Individual Effects

	Model 1	Model 2	Model 3	Model 4
F-statistics	66.462	98.293	11.636	19.221
p-value	< 0.01	< 0.01	< 0.01	< 0.01

Restricted F-Test for Time Effects

	Model 1	Model 2	Model 3	Model 4
F-statistics	12.598	1.744	0.959	3.609
p-value	< 0.01	< 0.01	0.47	< 0.01

Restricted F-Test for Two-Way Effects

	Model 1	Model 2	Model 4
F-statistics	29.962	31.469	18.254
p-value	< 0.01	< 0.01	< 0.01

Appendix B-5 Chi-square Statistics for Individual and Time Effects

	Model 1	Model 2	Model 3	Model 4
		Individual Effects		
F-statistics	187.480	53.241	8.020	72.748
p-value	< 0.01	< 0.01	0.09	< 0.01

Appendix B-5 (Continued)

	Model 1	Model 2	Model 4
	Time Effects		
F-statistics	925.600	62.735	188.570
p-value	< 0.01	< 0.01	<0.01

Appendix B-6 Regression Coefficients

Fixed-effect (Time) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures.

Variable	**Model 1 Effective Half Spread (t-statistics)**	**Model 2 Share Turnover (t-statistics)**	**Model 4 Amihud's illiquidity (t-statistics)**
Algorithmic trading	0.0011^{***}	$-1.4431\text{x}10^{-4***}$	$5.2930\text{x}10^{-6}$
	(25.669)	(-87.129)	(0.092)
Volatility	0.6094^{***}	0.0099^{***}	-0.0034^{**}
	(106.692)	(37.441)	(-2.285)
The inverse of price	0.0834^{***}	0.0025^{***}	-0.0290^{***}
	(15.236)	(9.631)	(-3.244)
Natural log of market cap	0.0190^{***}	-0.0029^{***}	-0.0153^{***}
	(17.848)	(-61.703)	(-9.042)
Share turnover	-4.6242^{***}		
	(-29.354)		
Adjusted R^2	45.89%	35.95%	16.01%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Random-effect (Individual) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures.

Variable	**Model 1 Effective Half Spread (t-statistics)**	**Model 2 Share Turnover (t-statistics)**	**Model 3 Liquidity Ratio (t-statistics)**	**Model 4 Amihud's illiquidity (t-statistics)**
Intercept	0.0367	0.0507***	-1,048.1391***	0.1552***
	(0.625)	(13.763)	(-5.930)	(3.794)
Algorithmic trading	0.0012***	-1.6171×10^{-4}***	-8.4957***	0.0003***
	(23.580)	(-94.235)	(-27.919)	(5.274)
Volatility	0.3743***	0.0081***	-60.5777***	0.0011
	(65.0442)	(33.935)	(-10.849)	(1.011)
The inverse of price	0.0160	-0.0072***	309.1104***	0.0107
	(0.618)	(-5.291)	(3.378)	(0.491)
Natural log of market cap	0.0102**	-0.0039***	73.8156***	-0.0086***
	(2.517)	(-15.232)	(5.908)	(-2.992)
Share turnover	-3.6829***			
	(-21.039)			
Adjusted R^2	23.35%	40.99%	56.12%	6.82%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Random-effect (Time) Regression Coefficients of Algorithmic Trading Proxy and Control Variables on Liquidity Measures.

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)	Model 4 Amihud's illiquidity (t-statistics)
Intercept	-0.1720***	0.0357***	0.2298***
	(-11.422)	(54.613)	(9.737)
Algorithmic trading	0.0011***	-1.4649×10^{-4}***	5.3456x10-5
	(25.717)	(-89.704)	(0.927)
Volatility	0.5838***	0.0099***	-0.0023
	(103.218)	(40.141)	(-1.606)
The inverse of price	0.0845***	0.0025***	-0.0291***
	(15.233)	(9.656)	(-3.215)
Natural log of market cap	0.0184***	-0.0029***	-0.0141***
	(17.089)	(-63.214)	(-8.297)
Share turnover	-4.6186***		
	(-29.013)		
Adjusted R^2	44.88%	38.47%	16.18%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Appendix B-7 Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors

Pooled OLS Regression Coefficients of Algorithmic Trading Initiated by Institutional and Foreign Investors Proxies and Control Variables on Liquidity Measures.

Variable	**Model 1 Effective Half Spread (t-statistics)**	**Model 2 Share Turnover (t-statistics)**	**Model 3 Liquidity Ratio (t-statistics)**	**Model 4 Amihud's illiquidity (t-statistics)**
Intercept	0.0124 (0.741)	0.0396*** (57.179)	-0.0010*** (-9.643)	0.2158*** (9.204)
AT initiated by institutional investors	1.8413×10^{-4}*** (9.693)	-3.7529×10^{-5}*** (-46.299)	-0.7875*** (-5.135)	1.6374×10^{-4}*** (4.793)
AT initiated by foreign investors	5.6417×10^{-4}*** (12.293)	-8.8973×10^{-5}*** (-45.329)	-1.2325*** (-2.817)	4.5411×10^{-4}*** (4.658)
AT initiated by institutional x foreign investors	2.0917×10^{-6}*** (9.569)	-1.8851×10^{-7}*** (-19.271)	0.0155*** (10.834)	2.3098×10^{-6}*** (7.244)
Volatility	0.5227*** (91.755)	0.0091*** (36.467)	-38.6576*** (-6.200)	-0.0009 (-0.679)
The inverse of price	0.1101*** (18.693)	8.0211×10^{-5} (0.301)	170.0326*** (4.308)	-0.0322*** (-3.661)
Natural log of market cap	0.0063*** (5.316)	-0.0031*** (-64.575)	78.7791*** (4.308)	-0.0121*** (-7.094)

Appendix B-7 (Continued)

Variable	Model 1 Effective Half Spread (t-statistics)	Model 2 Share Turnover (t-statistics)	Model 3 Liquidity Ratio (t-statistics)	Model 4 Amihud's illiquidity (t-statistics)
Share turnover	-5.8517^{***}			
	(9.569)			
Adjusted R^2	39.05%	38.29%	83.79%	20.58%

Note: *, ** and *** Denote Significance at the 10%, 5% and 1% Level.

Appendix B-8 Variance Inflation Factor during the Volatile Period

Daily Variables

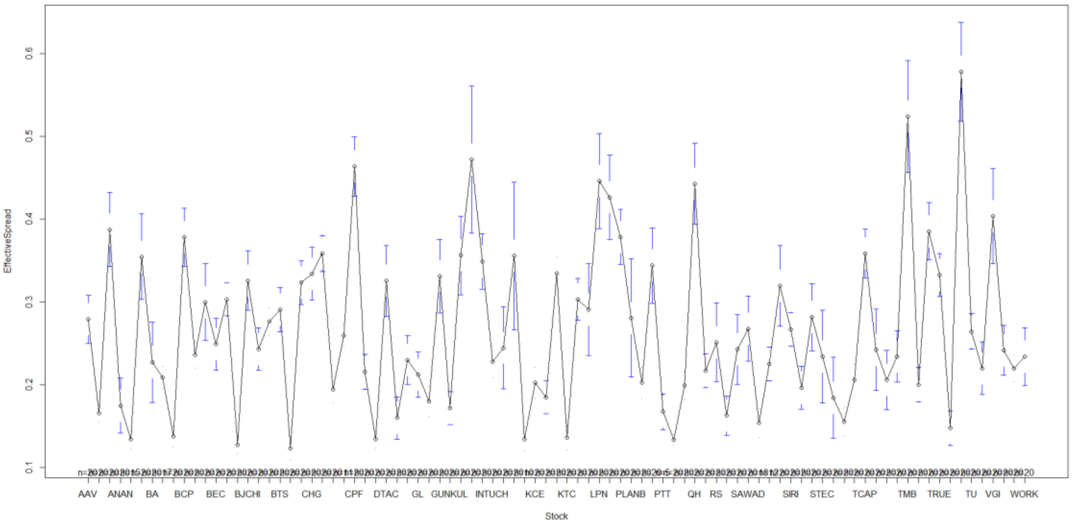
Algorithmic Trading	Realized Volatility	Share Turnover	Inverse of Price	Natural Log of Market Cap
3.1283	1.2147	1.9137	1.1722	2.5539

Monthly Variables

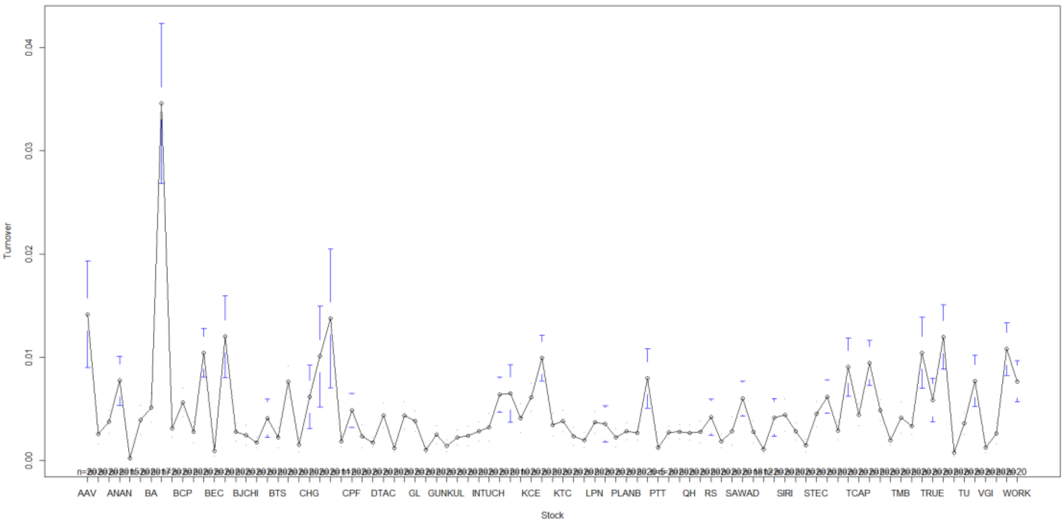
Algorithmic Trading	Realized Volatility	Inverse of Price	Natural Log of Market Cap
3.0567	1.5910	1.1683	4.0912

Appendix B-9 Stock Heterogeneity during the Volatile Period

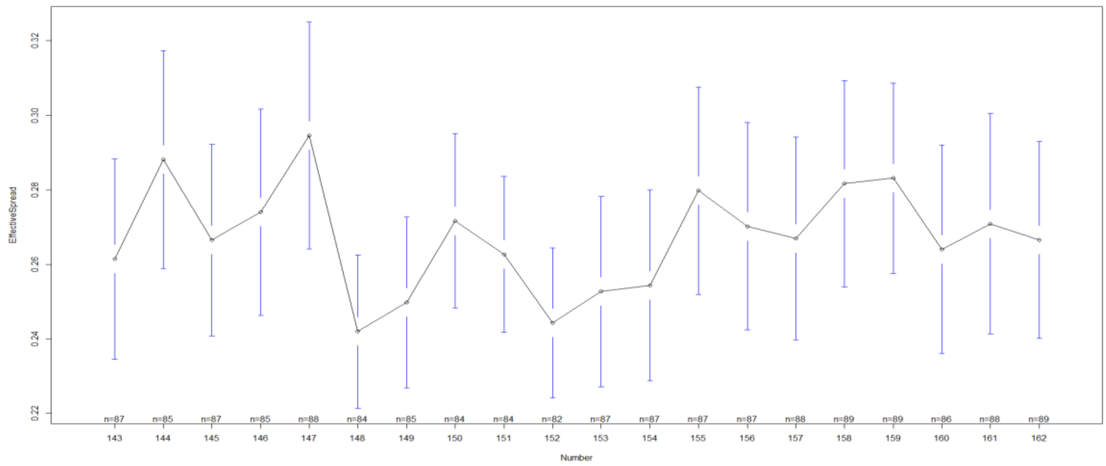
The mean plot of the effective spread across individual during the volatile period



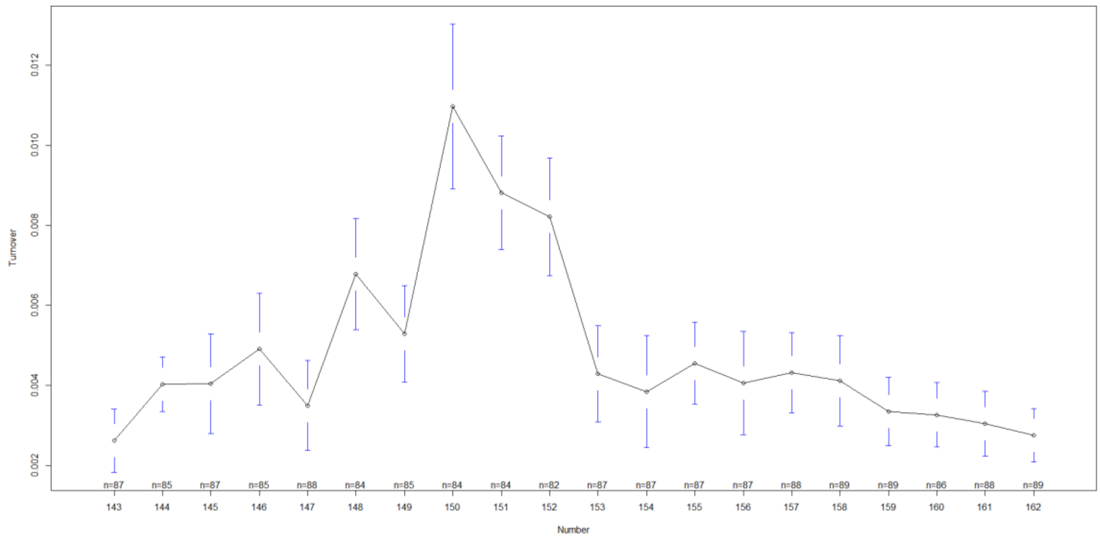
The mean plot of the share turnover across individual during the volatile period



The mean plot of the effective spread across time during the volatile period



The mean plot of the share turnover across time during the volatile period



Appendix B-10 Restricted F-test during the Volatile Period

Restricted F-test for Two-way Effects

	Model 1	**Model 2**
F-statistics	21.298	17.395
p-value	< 0.01	< 0.01

APPENDIX C

THE IMPACT OF ALGORITHMIC TRADING ON PRICE EFFICIENCY

APPENDIX C

THE IMPACT OF ALGORITHMIC TRADING ON PRICE EFFICIENCY

Appendix C-1 Hasbrouck (1993)'s variance of pricing error

In a market, there are informed and uninformed investors who have different set of private information. Investors signal their private information through trading. Thus, trade convey information. Hasbrouck (1991a) introduced the method to measure the information content of the stock prices using a vector autoregressive system. Hasbrouck (1991b) measured trade informativeness by measuring the variance of the trade-correlated components of the efficient price. However, these two methods required midpoints of the bid-ask quotes. Due to the lack of data, I therefore, used the method proposed by Hasbrouck (1993) which was the standard deviation of the pricing error, σ_s. Pricing error is the difference between transaction prices and efficient price. Pricing error is caused by microstructure effects such as discreteness, inventory component, information-uncorrelated noise etc. The standard deviation of the pricing error demonstrates how the prices track the efficient prices. The limitation of this measurement is that it only measures the pricing error of the trades that have already occurred, but it cannot reveal any information about quotes, forgone trade or private information.

Hasbrouck (1993) proposed a method to measure the pricing error, using the security transaction prices and volume. A nonstationary time-series of transaction prices consists of two components, namely, a random-walk component and a residual stationary component. Hasbrouck (1993), therefore, decomposes the logarithmic of the transaction price into these two components. The random walk or permanent component represents the efficient price, or the expected final value of the securities which incorporate all the publicly available information at time *t*. The residual stationary component is the pricing error or the different between actual transaction prices and efficient prices. Therefore, the logarithmic of the transaction price, p_t can be expressed as:

$$p_t = m_t + s_t$$

where m_t is the efficient price, s_t is the pricing error and t is the sequence of the transaction.

Two assumptions are made:

1) $m_t = m_{t-1} + w_t$,

where w_t is the uncorrelated increment.

2) The pricing error is covariance-stationary with a zero mean.

Hasbrouck (1993) defined the pricing error term as:

$$s_t = m_t - p_t = \alpha w_t + \eta_t$$

where w_t is the uncorrelated increment and the stationary component or pricing error can be decomposed into the information-correlated and information-uncorrelated components.

Moreover, it can be expressed as a function of trade volume (x_t):

$$s_t = \alpha x_t + \beta u_t + \eta_t,$$

where u_t is an innovation that is not derived from the trade and η_t is the residual that is uncorrelated with the trade (x_t) and other innovation that is not inferred from the trade (u_t).

Therefore, the return series is a regression with a moving-average error term. Hence, the model relating trades and price changes can be expressed using vector autoregression (VAR) as:

$$r_t = \sum_{i=1}^{10} a_i r_{t-i} + \sum_{i=1}^{10} b_i x_{t-i} + v_{1,t},$$

$$x_t = \sum_{i=1}^{10} c_i r_{t-i} + \sum_{i=1}^{10} d_i x_{t-i} + v_{2,t},$$

where r_t is the return $(p_t - p_{t-1})$ and for the purpose of this framework, x_t is the signed of the volume of trade variable. The sign is positive if it is a buyer-initiated trade and negative if it is a seller-initiated trade. $v_{1,t}$ and $v_{2,t}$ are the zero-mean and serially uncorrelated innovative disturbance terms, with $Var(v_{1,t}) = \sigma_1^2, Var(v_{2,t}) = \Omega$ and $E(v_{1,t}v_{2,t}) = 0$. This method does not account for heteroskedasticity. According to

Harris (1987), return heteroskedasticity can be mitigated by using the transaction time, instead of natural time.

As we are interested in the innovative disturbance terms, we transformed the VAR models into the vector moving average (VMA) models. Therefore, the return and the signed trade variables can be constituted as the functions of the current and lagged innovative disturbances. Therefore, the VMA models become:

$$r_t = \sum_{i=0}^{10} a_i^* v_{1,t-i} + \sum_{i=0}^{10} b_i^* v_{2,t-i},$$

$$x_t = \sum_{i=0}^{10} c_i^* v_{1,t-i} + \sum_{i=0}^{10} d_i^* v_{2,t-i},$$

or it can be written in term of lag operators as:

$$r_t = a^*(L)v_{1,t} + b^*(L)v_{2,t},$$

$$x_t = c^*(L)v_{1,t} + d^*(L)v_{2,t}.$$

This can be expressed in the matrices forms as:

$$y_t = \begin{bmatrix} r_t \\ x_t \end{bmatrix} = \theta(L)v_t = \begin{bmatrix} a^*(L) & b^*(L) \\ c^*(L) & d^*(L) \end{bmatrix}$$

As a result, the variance of the random-walk component is:

$$\sigma_w^2 = [\sum_{i=0}^{\infty} a_i^* \quad \sum_{i=0}^{\infty} b_i^*] Cov(v) \begin{bmatrix} \sum_{i=0}^{\infty} a_i^* \\ \sum_{i=0}^{\infty} b_i^{*'} \end{bmatrix}.$$

As the pricing error is defined as the function of information-correlated and information-uncorrelated terms, the pricing error variance is:

$$\sigma_s^2 = \alpha^2 \sigma_s^2 + \sigma_\eta^2,$$

For the ease of computation, by imposing the Beveridge and Nelson (1981) restriction, Hasbrouck (1993) established the lower bound for the variance of pricing error (σ_s^2) as:

$$VAR(Pricing\ Error) = \sigma_s^2 =$$

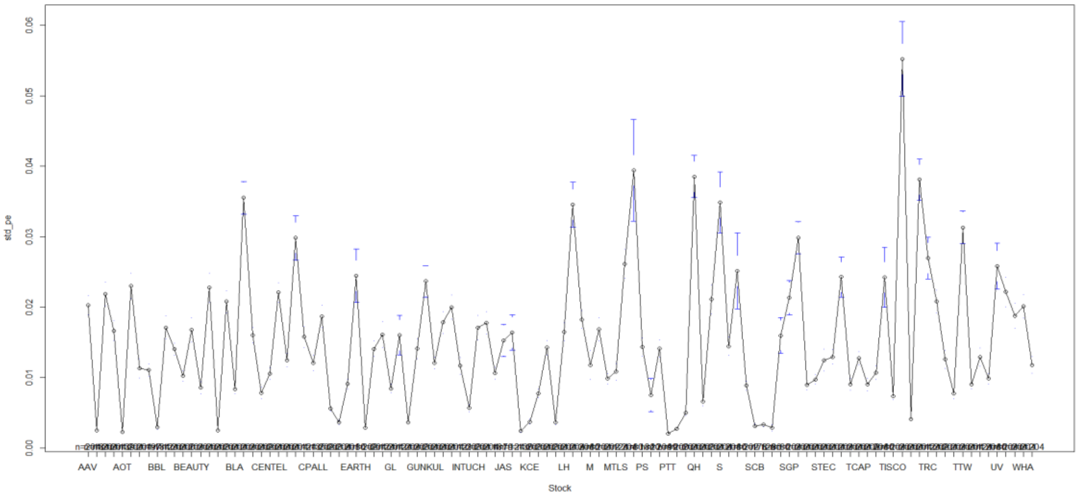
$$\sum_{j=0}^{\infty} [-\sum_{k=j+1}^{\infty} a_k^* \quad -\sum_{k=j+1}^{\infty} b_k^*] \, Cov(v) \begin{bmatrix} -\sum_{k=j+1}^{\infty} a_k^* \\ -\sum_{k=j+1}^{\infty} b_k^{*'} \end{bmatrix}.$$

Appendix C-2 Variance Inflation Factor (VIF)

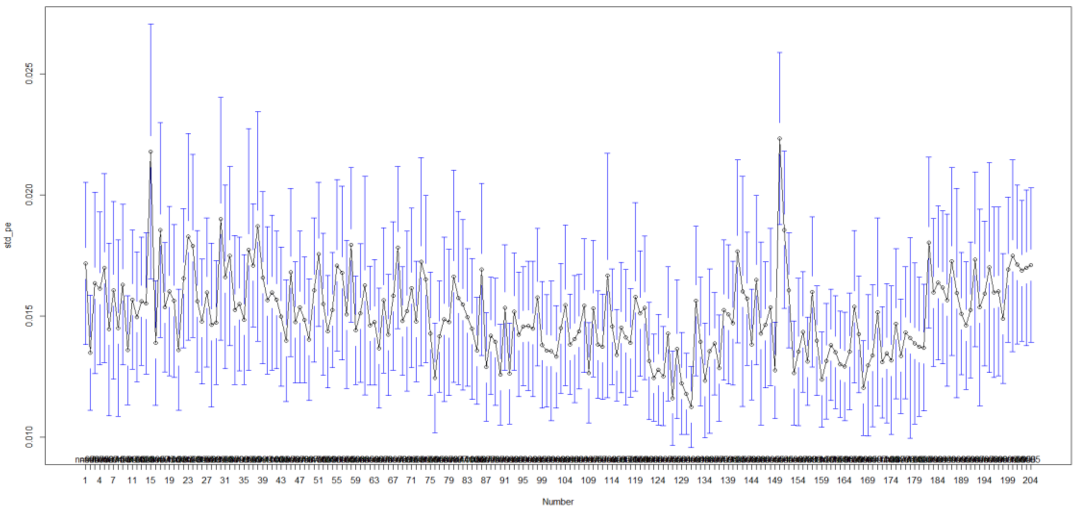
Algorithmic Trading	Realized Volatility	Share Turnover	Inverse of Price	Natural Log of Market Cap
2.0712	1.1553	1.3808	1.1612	1.9012

Appendix C-3 Stock Heterogeneity

The mean plot of the standard deviation of pricing error across individual



The mean plot of the standard deviation of pricing error across time



Appendix C-4 Restricted F-test

	Individual	Time	Twoways
F-statistics	32.252	2.854	12.859
p-value	< 0.01	< 0.01	< 0.01

Appendix C-5 Chi-square Statistics for Individual and Time Effects

	Individual	Time
F-statistics	40.383	153.49
p-value	< 0.01	< 0.01

Appendix C-6 Variance Inflation Factor

AT Initiated by Institutional Investors	AT Initiated by Foreign Investors	Realized Volatility	Share Turnover	Inverse of Price	Natural Log of Market Cap
3.6089	4.9794	1.1697	1.3798	1.1251	1.9568

Appendix C-7 Restricted F-Test

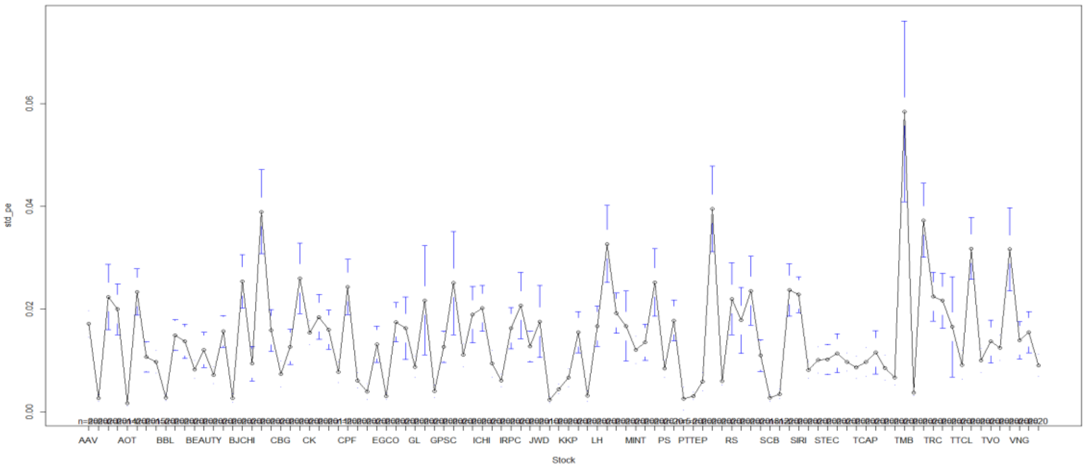
	Individual	Time	Twoways
F-statistics	29.985	2.843	12.025
p-value	< 0.01	< 0.01	< 0.01

Appendix C-8 Chi-square Statistics

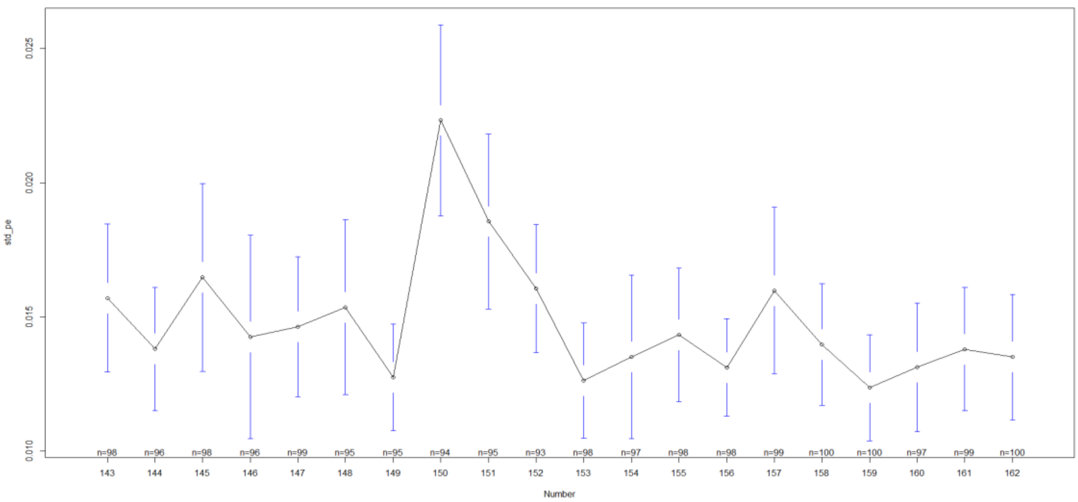
	Model 1	Model 2
F-statistics	45.473	57.505
p-value	< 0.01	< 0.01

Appendix C-9 Stock Heterogeneity during the Volatile Period

The mean plot of the standard deviation of pricing error across individual during the volatile period



The mean plot of the standard deviation of pricing error across time during the volatile period



Appendix C-10 Restricted F-test during the Volatile Period

	Individual	Time	Twoways
F-statistics	6.747	2.984	6.012
p-value	< 0.01	< 0.01	< 0.01

Appendix C-11 Chi-square Statistics for Individual and Time effects during the Volatile Period

	Model 1	Model 2
F-statistics	42.176	28.096
p-value	< 0.01	< 0.01

BIOGRAPHY

NAME	Miss Pavinee Hassavayukul
ACADEMIC BACKGROUND	Bachelor's Degree in Electrical and Computer Engineering from Carnegie Mellon University in 2007, and a Master's Degree in Electrical and Computer Engineering from Carnegie Mellon University in 2007
PRESENT POSITION	Deputy Managing Director at PVN Engineering Co., Ltd and PAWIN Engineering Co., Ltd. Business Development Director and Co-Founder at Axiom Development Co., Ltd.