High Frequency Trading and Market Quality in the Thai Stock Exchange

Surachai Chancharat and Pongsutti Phuensane*

Abstract— *This research is based on an empirical analysis of the impact of HFT activity on the stock in the SET50 index trading in the Stock Exchange of Thailand (SET), using publicly-available trade-by-trade tick data for the period between January 01, 2016 and June 30, 2018. The HFT data is illustrated to show the pattern of the HFT orders in the SET with a strong relationship between HFT orders and the market quality. Also, the OLS analysis shows that most market quality proxies such as the effective spread, realized spread, and price impact has a negative relationship with the number of HFT orders. This indicates that the level of the effective spread realized spread, and price impact is reduced when the HFT activity increases.*

Keywords— **HFT, market microstructure, market quality, SET50.**

1. INTRODUCTION

The technological revolution has changed the financial trading process from beginning end, and this change has transformed the entire trading system from order entry to trading venue, matching process, and lately, back office. These fully automated functions dramatically reduce the trading costs of all agents in the venue [1]. This financialization has continued to improve over the past decade and has been applied across the world. The use of robot trading, known as High Frequency Trading (HFT), which is one of the Algorithmic Trading (AT) strategies, has increased, and when the trading strategy reaches a very high speed of order adjustment, HFT will be mentioned. The speed of HFT is as fast as the blink of a human eye. This means that the order message can be sent and executed in a very short period of time, usually in a millisecond. It was found in a previous study that the shortest order update was 60 microseconds for the E-mini S&P 500 [2].

HFT based on AT is a computerized system for the execution of buying or selling orders in a way that is expected to eliminate the risk of human intervention [3]. HFT is generally considered to be a subset of AT. This means that all kinds of HFT are AT, but not vice versa. Previous studies have shown that HFT helps to increase liquidity; hence, it facilitates better decision making in terms of time, price and volume. The increased liquidity leads to a decrease in spread, effective spread, and price impact. These narrow metrics mean that HFT can improve the quality of the market [4]. However, the increased liquidity from HFT is sometimes accompanied by a flow of toxic liquidity, which causes the market to crash, such as the flash crash on May 6th, 2010 [5], [6]. Reference [7] also argued that, although HFT helps to improve the liquidity in the market, this tremendous liquidity makes the market unstable.

Therefore, the advantages and disadvantages of HFT are increasingly being debated, not only by academics, but also practitioners. While the impact of HFT on the quality of the market has gained momentum in global financial studies, there has been no comparable level of study by Thai researchers to date. There is a limited number of studies on AT, but no more than 20 papers have been published on HFT since 2007, which is the year that the Stock Exchange of Thailand (SET) allowed its clients to use machines to submit orders to the market. Despite the shortage of research on AT and HFT in the SET, this topic is gaining popularity since the SET began to urge securities companies and institutional investors to adopt AT for their trading.

This research is intended to complement the theoretical and empirical literature of the market microstructure on the electronic quote and trade for High Frequency Trading (HFT). Reference [8] and [9] examined a number of HFT activities and found that HFT is more likely to increase liquidity on the demand side when the spreads are wide and on the supply side when they are narrow. Reference [1] studied the role of HFT and price discovery, while [10] analyzed HFT when they explained the hot potato effect on the event of May 6th, 2010, known as a ``flash crash" in the E-Mini S&P 500.

The impact of HFT on the quality of the market has been studied by [1], [11] examined the activity of HFT in the New York Stock Exchange and the Deutsche Boerse market and found that HFT narrows spreads, reduces adverse selection, and reduces trade-related price discovery. Reference [12] also studied the effect of low-latency activity on market quality. Moreover, [7] argued that the effect of HFT is due to its strategies. In contrast, only two papers have been found on the study of AT and HFT in the Thai stock market. One of them is the study

Surachai Chancharat and Pongsutti Phuensane are with Faculty of Business Administration and Accountancy, Khon Kaen University, 123 Mitrapab Rd., Nai Muang, Khon Kaen, 40002 Thailand and Durham University Business School, Durham University, UK. Thailand.

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*Corresponding author: Pongsutti Phuensane, Phone: +6643-202-401; Fax: +6643-202-402; E-mail: pongphu@kku.ac.th.

of [13] on how AT uses a unique data set from the SET. He discovered a positive relationship between AT and volatility and also that AT helps to improve welfare by increasing liquidity and lowering trading costs. The other paper belongs to [14] who used private data from the SET to find that AT orders are followed by human orders, but not the other way round. ATs tend to use market orders when the order is small and chase after positive returns, whereas they are likely to use limited orders when the order is large, past volume is high or exhibits high volatility.

This work has three objectives: 1) to develop the knowledge of market microstructure based on a study of HFT for the financial research community in Thailand, 2) to study the market mechanism on the Stock Exchange of Thailand when HFT is operated in the market, and 3) to discover the impact of HFT on the Stock Exchange of Thailand and whether increasing it is beneficial to the market quality as well as the welfare of all the participants.

This research aims to contribute to helping the Securities and Exchange Commission Thailand (SEC) to develop a new system to protect it from the liquidity risk and flow of toxicity as a result of increasing HFT activity. It also includes a comprehensive and innovative HFT detection algorithm based on data from the Stock Exchange of Thailand, which is more comprehensive than trade data. Moreover, this detection algorithm, constructed from publicly-available data, will be available for other researchers to implement in studies in a different market setting. Finally, the results of this study can be of great potential for Thai financial regulators to study and apply the findings to create new rules for HFT.

The remainder of the study is organized as follows. The second section contains a review of the literature on HFT and market quality, while the adaptation of the HFT detection algorithm and market quality proxies are presented in the third section, along with the OLS model. The fourth section contains an analysis of the dataset, and finally, the key findings are summarized in the fifth section with some brief concluding comments and proposed directions for future research.

2. REVIEW OF MARKET QUALITY AND HIGH-FREQUENCY TRADING SUBMISSION

There is still a limited amount of research on the impact of HFT or AT on the quality of the financial market in emerging markets. The most common paper on this topic is that of [1], who argue that AT improves the liquidity of the NYSE, which reduces the costs of traders. Chordia et al. (2011) also discovered that increased trading activity improved the price efficiency of securities. However, [16] argued that the effect of algorithmic trading on the quality of the market depends on the type of algorithm activity.

The positive effect of ATs is increasingly debated, and [12] found that ATs have a positive effect of reducing the market impact and trading costs when institutional investors use them for proprietary trading and they trade large volumes of shares. Also, [17] found that HFT firms enhance the market quality as liquidity providers. However, some studies show that ATs have a negative effect, such as that of [18], who argues that there is no clear evidence that HFT affects institutional execution costs. Reference [19] also shows that HFT activity can be harmful during times of extreme market stress.

The knowledge of HFTs is still limited, especially in emerging markets like Thailand, because the HFT orders are hard to identify [14]. Most HFT researchers used specific or private datasets; for instance, [20] used private data from Morgan Stanley to determine the risk of execution costs and the time taken to identify which order might be planned and executed using an algorithmic trading system. They used a novel dataset which was not publicly available; therefore, [1], [19], [21] overcame this problem by using the volume of electronic message traffic or the number of message updates per minute on trading day as a proxy of HFT orders.

The lack of data is not the only significant issue for HFT researchers, but also the limited knowledge of HFT detection algorithms to identify HFT orders. Some of the early researchers of this topic used the normalized volume of electronic message traffic as a proxy for ATs. [1], [21]. This work will also follow [1] to identify the number of HFT orders in the Stock Exchange of Thailand, known as the SET, to determine whether the liquidity flow from fast trading is beneficial or harmful to the market.

Research Data

The data used in this research is introduced in this section. Since the research is focused on the market microstructure, the data collection is ubiquitous, especially high-frequency data. Most HFT researchers have used a unique dataset, whereas the data for this research is publicly available from the Stock Exchange of Thailand. The trade and quote data is collected from Thomson Reuters Tick History (TRTH) database, which contains the tick data of Trade and Quote data in a millisecond timestamp in order to determine the transmission and storage of the data.

The updated HFT data recorded in microseconds taken from Thomson Reuters Tick History (TRTH) is shown in Table 1. It contains the RIC code, time stamp (recorded in milliseconds), bid price, bid size, ask price, ask size, trade price and trade volume. The raw data is divided into three files. The first is the bid data, the second is the ask data, and the third is the trade data. A cleaning procedure was used to clean any unnecessary data, such as N/A, duplicate data, missing values, after which the steps to clean, pre-process, integrate and feature the collected data were selected. These steps constitute an important preparation phase for a big data financial analysis. The trade and quote data were then merged into one file and the mid-price was calculated by VWAP with the trading direction as shown in Table 1. This step involved developing the data structure. The data was then visualized and prepared for the next step to develop the HFT detection algorithm in the stock market and a mathematical model to analyze the impact of HFT on the market quality. The findings from all of these steps were finally used to adjust the rules or regulations to protect the market from the impact of HFT.

Table 1. Example of SET tapes data recorded in millisecond time stamp

	ric	date	bp	bs	ap	as	tp	ts	side	midp
1	TCAP.BK	2015-01-05T09:30:05.456263000+07	31.50	200000	32.75	3000	NA	NA	NA	NA
2	TCAP.BK	2015-01-05T09:30:05.510959000+07	31.75	100000	32.75	3000	NA	NA	NA	NA
3	TCAP.BK	2015-01-05T09:30:05.736529000+07	31.75	100000	32.00	30000	NA	NA	NA	NA
4	TCAP.BK	2015-01-05T09:30:06.132969000+07	31.75	150000	32.00	30000	NA	NA	NA	NA
5	TCAP.BK	2015-01-05T09:30:06.390790000+07	31.75	170000	32.00	30000	NA	NA	NA	NA
6	TCAP.BK	2015-01-05T09:30:06.424959000+07	31.75	175000	32.00	30000	NA	NA	NA	NA
7	TCAP.BK	2015-01-05T09:30:08.078290000+07	33.50	1800	32.00	30000	NA	NA	NA	NA
8	TCAP.BK	2015-01-05T09:30:26.554600000+07	33.50	1800	32.00	30500	NA	NA	NA	NA
9	tcap.BK	2015-01-05T09:57:17.014203000+07	NA	NA	NA	NA	32.00	35700	buy	32.750
10	TCAP.BK	2015-01-05T09:57:17.025925000+07	31.75	403000	32.00	93500	NA	NA	NA	NA
11	tcap.BK	2015-01-05T09:57:17.058158000+07	NA	NA	NA	NA	32.00	93500	buy	31.875
12	TCAP.BK	2015-01-05T09:57:17.058158000+07	32.00	27800	32.25	116300	NA	NA	NA	NA
13	TCAP.BK	2015-01-05T09:57:17.130417000+07	32.00	30300	32.25	116300	NA	NA	NA	NA
14	TCAP.BK	2015-01-05T09:57:19.346256000+07	32.00	31300	32.25	116300	NA	NA	NA	NA
15	TCAP.BK	2015-01-05T09:57:19.356006000+07	32.00	32900	32.25	116700	NA	NA	NA	NA
16	tcap.BK	2015-01-05T09:57:22.804122000+07	NA	NA	NA	NA	32.25	200	buy	32.125
17	TCAP.BK	2015-01-05T09:57:22.826583000+07	32.00	32700	32.25	116500	NA	NA	NA	NA
18	tcap.BK	2015-01-05T09:57:23.256292000+07	NA	NA	NA	NA	32.25	200	buy	32.125
19	TCAP.BK	2015-01-05T09:57:23.256292000+07	32.00	32700	32.25	116300	NA	NA	NA	NA
20	tcap.BK	2015-01-05T09:57:23.835354000+07	NA	NA	NA	NA	32.25	200	buy	32.125
21	TCAP.BK	2015-01-05T09:57:23.857852000+07	32.00	32700	32.25	116100	NA	NA	NA	NA

Note: This table shows the tapes data that recorded in millisecond time stamp of HFT data for TCAP stock traded in the SET. This data set include ric code, date and time stamp, bid price, bid size, ask price, ask size, trade, price, trade size, trade direction and quote mid-price.

3. METHODOLOGY

The methodology used to complete this work will be introduced in this section, such as how to identify an HFT message or the proxies of an HFT message, and the liquidity measures, which include the quoted spread, effective spread, realized spread and price impact. The OLS model used to describe the impact of HFT orders on market quality will finally be explained.

Proxies of HFT messages

The determination of the HFT detection algorithm was challenging, because it is generally impossible to directly identify whether the order is generated by a computer algorithm or human finger using a publicly-accessible dataset. The HFT participation was calculated based on the framework of [1], [11] using the Hendershott approach, which is the use of updated raw messages and the volume of orders. An order is classified as an HFT order if more than 250 messages are updated per minute or the speed of the order is faster than 250 milliseconds, i.e., as fast as the blink of an eye. Since it is impossible for a human to send 4 orders in one minute at this speed (4 orders per minute), the period of time between the order at time t and the order at time t+1 will be calculated, and the order will be classified as an HFT order if the time difference is shorter than 250 milliseconds.

Market Quality and Liquidity measures

The liquidity and market quality will be measured in this section based on the quoted spread, effective spread, realized spread and price impact. The mid-price from the normal quoted spread will be used to calculate this measurement. The quoted spread is the difference between the ask price (AP_t) and the bid price (BP_t) divided by the mid-price (mid_t). The effective spread is the difference between the midpoint from AP_t and BP_t, and the trade price. The Effective spread is used to measure the market condition because it captures the liquidity flow; for instance, a wider effective spread means that the market has less liquidity and less quality. Hendershott recommend the use of this spread to traders or institutions who want to trade at the inside quote because the effective spread is more meaningful than the normal spread as a transaction cost at the point of execution. Therefore, the proportion of the quoted spread can be defined by the following equation;

$$\mathrm{Spread_t} = \frac{\mathrm{AP_t - BP_t}}{\mathrm{mid_t}} \tag{1}$$

and effective spread defined as:

$$\mathrm{Effecive\ Spread_t} = \frac{\mathrm{TD_t(TP_t - mid_t)}}{\mathrm{mid_t}} \tag{2}$$

where TD_t is signed-trade direction indicator that equals 1 for buy-initiated and -1 for sell-initiated.

The Effective Spread (effspread) can be divided into two components. The first is the Realized Spread (realspread), which represents the theoretical profit of a liquidity provider or a cost for liquidity suppliers who want to keep their position at the midpoint after a trade. The realspread is defined as follows;

$$\mathrm{Realized\ Spread_t} = \frac{\mathrm{TD_t(TP_t - mid_t)}}{\mathrm{mid_{t+1}}} \tag{3}$$

where TP_t is trade price, TD_t is trade indicator, and mid_t is midpoint from VWAP approach.

The second component is the adverse selection measured by price impact (priceimpact). The priceimpact shows how much the mid-price moves within a given look-ahead window. It can also be represented as the liquidity suppliers loss to informed traders due to adverse selection [22]. This work uses the next midpoint instead of time windows; therefore, the priceimpact is defined as follows;

$$\mathrm{Price\ Impact} = \frac{\mathrm{TD_t(mid_{t+1} - mid_t)}}{\mathrm{mid_t}} \tag{4}$$

This effspread, realspread, and priceimpact is a standard measurement of market liquidity and market quality; hence, when this metric becomes narrow, it can be assumed that the market has more liquidity and quality [15].

The OLS model

The OLS from [12] is adapted to determine the effect of High-Frequency Trading on market liquidity and market quality in this study. It is assumed that HFT will have a negative relationship with market quality; for example, when the market quality improves, the realized spread should decrease, as shown in the literature. However, the results of this study will tell the whole story. Therefore, the OLS model is as follows;

$$\mathrm{MQ_i} = \alpha + \beta_1 \mathrm{HFT_i} + \beta_2 \mathrm{Return_i} + \beta_3 \mathrm{Volatility_i} + \sigma \tag{5}$$

where $i = 1, \ldots, n$ indexes the number of stock, MQ_i represents one of the market quality measures (Spread, Effective Spread, Realized Spread, and Price Impact), and HFT_i is the number of HFT orders per day. $Return_i$ and $Volatility_i$ are the return and volatility of stock i.

4. ANALYSIS

Number of electronic messages per day

Before analyzing the impact of HFT on the Stock Exchange of Thailand, the number of orders and electronic messages per day between January 01, 2016 and June 30, 2018 taken from the SET 50 data, is summarized in Fig.1. It can be seen that the average number of orders per day was 3,025 and the highest number of electronic messages per day was 61,614, while the lowest was 53. It can also be seen from the Fig.2. that the average number of messages for SET 50 stock from 2016 to 2018 moved from around 2,000 to 5,000 per day. There were around 3,000 messages per day in 2016, which then dropped to around 2,000 in 2017.

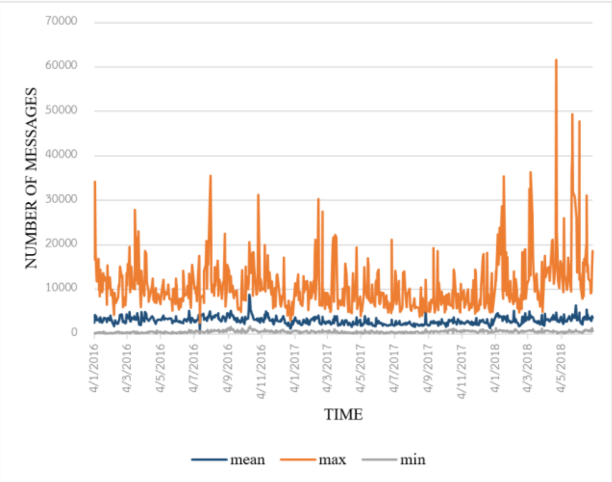

Fig. 1. Number of electronic messages per day.

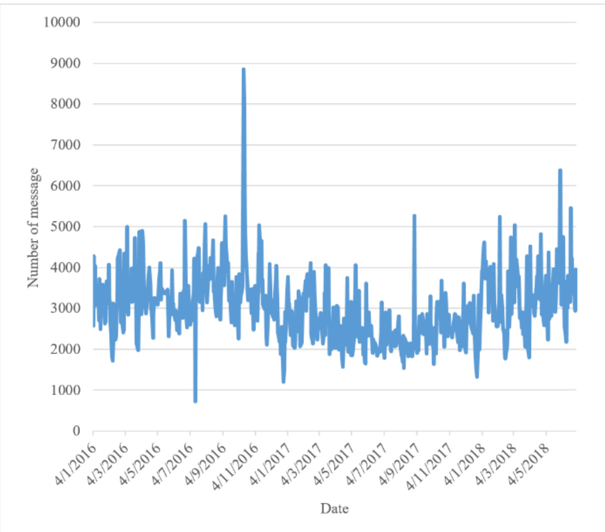

Fig.2. Average number of electronic messages per day.

The lowest average number of messages per day were around January, 2017, when it stayed below 3,000 for most of the year. After 2017, the number of messages per day increased from about 2,500 to around 3,000 in January 2018, and then reached 4,000 per day in March 2017. It reached its highest peak with about 6,500 messages per day in May 2017. This pattern of the number of messages is consistent with the market quality measures, which will be explained in the next section.

Market Quality

The market quality measures will be incorporated with the number of messages per day for the analysis. The market quality is normally measured based on Quote Spread, Effective Spread, Realized Spread and Price Impact. An interesting pattern of the market quality measures was found before they were analyzed. It can be seen from Fig.3. that the level of market quality measures, such as the effective spread, realized spread and price impact, have a similar curve, since this tree shows an increase from the beginning of 2016, which then reaches a peak around May 2016 before dropping to the bottom around July 2016. After July 2016, the three proxies' increase again to reach a peak around the end of March 2017, which this peak is the highest for the whole period. Then, the Spread, Realized Spread and Price Impact slightly decrease until the end of June 2018.

Fig.3. Market Quality Measures.

HFT messages vs. market quality based on an OLS

An OLS regression was used to investigate the impact of HFT messages on market quality. Therefore, the model was $\mathrm{MQ_i} = \alpha + \beta_1 \mathrm{HFT_i} + \beta_2 \mathrm{Return_i} + \beta_3 \mathrm{Volatility_i} + \sigma$, the coefficient estimates were OLS, p-value and R-squared. The results are reported in four different tables showing the impact on the market quality of spread, effective spread, realized spread and price.

The first panel in Table 1 shows the results for $Spread_i = \alpha + \beta_1 HFT_i + \beta_2 Return_i + \beta_3 Volatility_i + \sigma$. It can be seen that that the coefficient for HFT messages had a positive effect on spread with an β_1 of 2.78e-06 and it was statistically significantly different from 0 using an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. Next, the coefficient for return had a positive effect on spread with an β_2 of 0.78 and it was statistically significantly different from 0 using an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. This table also shows the coefficient for volatility, which had a positive effect on spread with an β_3 of 0.88; however, this was not statistically significant at the 0.05 level, since the p-value was greater than .05. Lastly, the coefficient of the value of the consistency of this regression model was -0.75.

Table 2. The result of

$$\mathbf{MQ_i = \alpha + \beta_1 HFT_i + \beta_2 Return_i + \beta_3 Volatility_i + \sigma}$$

t-ststistics using robus, standard errors are in brackets.
****p< 0.01, **p< 0.05, *p< 0.*

		1 (HFT)	2 (Return)	3 (Volatility)
Spread	*Coef.*	2.78E-06	2.78E-01	8.82E-01
	(p-value)	0.000**	0.000***	0.116
	Std. Err.	[6.87E-07]	[1.50E-03]	[5.61E-01]
Effective Spread	*Coef.*	-5.62E-08	-3.27E-04	-3.36E-02
	(p-value)	0.000***	0.000***	0.000***
	Std. Err.	[1.60E-09]	[3.51E-06]	[1.31E-03]
Realized Spread	*Coef.*	-3.04E-08	-3.28E-04	-3.37E-02
	(p-value)	0.000***	0.000***	0.000***
	Std. Err.	[1.60E-09]	[3.51E-06]	[1.31E-03]
Price Impact	*Coef.*	-8.14E-09	-1.77E-05	1.71E-02
	(p-value)	0.000***	0.000***	0.000***
	Std. Err.	[3.67E-10]	[8.04E-07]	[2.99E-04]

Note: This table presenting pooled panel regression analizes the relationship between HFT messages and market quality.

The second panel in Table 1 shows the results for the $Effective\ Spread_i = \alpha + \beta_1\ HFT_i + \beta_2\ Return_i + \beta_3\ Volatility_i + \sigma,$ which illustrates that the coefficient for HFT messages had a negative effect on spread with an β_1 of -5.62e-08, and it was statistically significantly different from 0 using an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. Next, the coefficient for return had a negative effect in spread with an β_2 of -0.0003, and it was statistically significantly different from 0 using an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. This table also shows the coefficient for volatility, which had a positive effect on spread with an β_3 of 0.0057; however, this was not statistically significant at the 0.05 level since the p-value was greater than .05. Lastly, the coefficient of the value of the consistency of this regression model was 00032.

The third panel in Table 1 shows the results of the $Realized\ Spread_i = \alpha + \beta_1\ HFT_i + \beta_2\ Return_i + \beta_3\ Volatility_i + \sigma.$ It can be seen from the coefficient of HFT messages that this had a negative effect on spread with an β_1 of -3.04e-08, and it was statistically significantly different from 0 using an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. Next, the coefficient of return shows that this had a negative effect on spread with an β_2 of -0.0003, and it was statistically significantly different from 0 using an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. This table also shows the coefficient for volatility, which was found to have a positive effect on spread with an β_3 of -0.0336; however, this was not statistically significant at the 0.05 level since the p-value was greater than .05. Lastly, the coefficient of the value of consistency of this regression model was 0026.

The last panel in Table 1 shows the results of $Price\ Impact_i = \alpha + \beta_1 HFT_i + \beta_2 Return_i + \beta_3\ Volatility_i + \sigma.$ It can be seen from the coefficient of HFT messages that this had a negative effect on spread with an β_1 of -8.144e-09, and it was statistically significantly different from 0 using an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. Next, the coefficient of return showed a negative effect on spread with an β_2 of -0.00001, and it was statistically significantly different from 0 with an alpha of 0.05 because its p-value was 0.000, which is smaller than 0.05. This table also shows the coefficient of volatility, which was found to have a positive effect on spread with an β_3 of 0.017; however, this was not statistically significant at the 0.05 level since the p-value was greater than .05. Lastly, the coefficient of the value of consistency of this regression model was 0.00019.

5. CONCLUSION

This research consisted of an empirical analysis of the impact of HFT activity on the stock in the SET50 index trading on the Stock Exchange of Thailand, using publicly-available trade-by-trade data. It was found from a literature review that the HFT is one of the algorithm trading strategies that create more liquidity in the stock market, and this liquidity tends to improve the quality of the market. Firstly, the average number of HFT messages over the period from January 01, 2016 until June 30, 2018 was illustrated to show the pattern of HFT orders. Secondly, a plot of market quality measures over the same time period was illustrated. These two figures showed that there is a strong relationship between the average number of HFT messages and market quality measures. Then, an OLS was used to analyze the impact of HFT messages on market quality measures, such as the quoted spread, effective spread, realized spread, and price.

The results of the coefficient estimates from the OLS can be interpreted as HFT messages having a causual impact on market quality. The results show that, while HFT messages (HFT) were positively related to the quoted spread (Spread), they were negatively related to the Effective Spread, Realized Spread, and Price over the related period. The positive association of HFT orders and Spread may be explained by the nature of the HFT algorithm trading strategy whereby most orders tend to be submitted when the quoted spread is wide. This result is consistent with [1], [11], [19]. Furthermore, the contemporaneous negative relationship between HFT messages and effective spread indicates that the effective spread tends to be narrow when HFT activity is increased. This result is consistent with [23]. Also, the contemporaneous negative relationship between HFT activity and realized spread indicates that, when the transitory price movement or liquidity is reduced, suppliers potentially suffer a short-term trading loss due to an adverse price move after the trade when the number of HFT message is high [25], [24]. This result is consistent with [18], [19], [26]. Finally, there is a significant contemporaneous negative relationship between HFT messages and price impact, indicating that hidden orders reduce the level of information asymmetry in the Thai stock market.

At this point, the results of the OLS in the last section show that most of the market quality proxies, such as the effective spread, realized spread, and price, have a negative association with the number of HFT messages. This negative relationship indicates that the level of the effective spread realized spread and price impact is reduced when there is an increase in HFT activity.

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REFERENCES

[1] Hendershott, T.; Jones, C.M.; and Menkveld, A.J. 2011. Does algorithmic trading improve liquidity?. *The Journal of finance* 66(1):1-33.

[2] Phuensane, P. and Williams, J.M. 2016. Term-structure analysis of hidden order in the limit order book: evidence from the E-Mini S&P 500. Available at SSRN: https://ssrn.com/abstract=2852760.

[3] Johnson, B., 2010. *Algorithmic Trading & DMA: An introduction to direct access trading strategies*. London: 4Myeloma Press.

[4] Chordia, T.; Roll, R.; and Subrahmanyam, A. 2008. Liquidity and market efficiency. *Journal of Financial Economics* 87(2): 249-268.

[5] Dubey, R.K.; Chauhan, Y.; and Syamala, S.R. 2017. Evidence of algorithmic trading from Indian equity market: Interpreting the transaction velocity element of financialization. *Research in International Business and Finance* 42: 31-38.

[6] Easley, D.; De Prado, M.M.L.; and O'Hara, M. 2011. The microstructure of the "flash crash": flow toxicity, liquidity crashes, and the probability of informed trading. *The Journal of Portfolio Management* 37(2):118-128.

[7] Biais, B. and Foucault, T. 2014. HFT and market quality. *Bankers, Markets & Investors* (128): 5-19.

[8] Brogaard, J. 2010. High frequency trading and its impact on market quality. *Working Paper*. Northwestern University Kellogg School of Management.

[9] Brogaard, J. 2011. The activity of high frequency traders. *Working Paper.* University of Washington.

[10] Kirilenko, A.; Kyle, A.S.; Samadi, M.; and Tuzun, T. 2017. The flash crash: High-frequency trading in an electronic market. *The Journal of Finance* 72(3): 967-998.

[11] Hendershott, T. and Riordan, R. 2013. Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis* 48(4):1001-1024.

[12] Hasbrouck, J. and Saar, G. 2013. Low-latency trading. *Journal of Financial Markets* 16(4): 646-679.

[13] Wajanawichakorn, P. 2013. Algorithmic Trading: Liquidity and Volatility. Faculty of Commerce and Accountancy, Thammasat University.

[14] Likitapiwat, T. 2016. Algorithmic Trading in an Emerging Market: Empirical Study on the Stock Exchange of Thailand. *CMRI Working Paper 1/2016*. Stock Exchange of Thailand.

[15] Chordia, T.; Roll, R.; and Subrahmanyam, A. 2011. Recent trends in trading activity and market quality. *Journal of Financial Economics* 101(2): 243-263.

[16] Scholtus, M.; Van Dijk, D.; and Frijns, B. 2014. Speed, algorithmic trading, and market quality around macroeconomic news announcements. *Journal of Banking & Finance* 38: 89-105.

[17] Subrahmanyam, A. and Zheng, H. 2016. Limit order placement by high-frequency traders. *Borsa Istanbul Review* 16(4): 185-209.

[18] Brogaard, J.; Hendershott, T.; Hunt, S.; and Ysusi, C. 2014. High-frequency trading and the execution costs of institutional investors. *Financial Review* 49(2): 345-369.

[19] Brogaard, J.; Hendershott, T.; and Riordan, R. 2014. High-frequency trading and price discovery. *The Review of Financial Studies* 27(8): 2267-2306.

[20] Robert, E.; Robert, F.; and Jeffrey, R. 2012. Measuring and modeling execution cost and risk. *The Journal of Portfolio Management* 38(2): 14-28.

[21] Boehmer, E.; Fong, K.; and Wu, J. 2012, March. International evidence on algorithmic trading. *The AFA 2013 San Diego Meetings Paper*. Available at SSRN: https://ssrn.com/abstract=2022034.

[22] Chakrabarty, B.; Pascual, R.; and Shkilko, A. 2015. Evaluating trade classification algorithms: Bulk volume classification versus the tick rule and the Lee-Ready algorithm. *Journal of Financial Markets* 25: 52-79.

[23] Menkveld, A.J. 2013. High frequency trading and the new market makers. *Journal of financial Markets* 16(4): 712-740.

[24] Zhang, S.S. and Riordan, R. 2011. Technology and market quality: The case of high frequency trading. In Proceedings of *19th European Conference on Information Systems*. Helsingi: Finland, 9-11 June. Illinois: The Association for Information System.

[25] U.S. Securities and Exchange Commission. (2014). Equity market structure literature review Part II: High frequency trading. Staff of the Division of Trading and Markets.

[26] Riordan, R. and Storkenmaier, A. 2012. Latency, liquidity and price discovery. *Journal of Financial Markets* 15(4): 416-437.