DOES ALGORITHMIC TRADING IMPROVE LIQUIDITY IN EMERGING MARKETS? EMPIRICAL EVIDENCE FROM THAILAND

Pavinee Hassavayukul[1,*]

ABSTRACT

This study explores the impact of algorithmic trading (AT) on liquidity in Thailand, as it affects both investors' welfare and the cost of capital for firms. Empirical studies on this topic in emerging markets are scarce. A panel data analysis and two-stage least square regressions on the stocks of the SET100 listed on the Stock Exchange of Thailand from March to December 2016, were used to establish the relationship between AT and liquidity. The results showed that AT causes liquidity to deteriorate by enlarging the effective half spread, decreasing share turnover, increasing Amihud's illiquidity estimate, and lowering the liquidity ratio. Various methods were employed to alleviate endogeneity issues. The results indicated that liquidity declines due to information asymmetry. This study was the first to investigate the effect of AT (initiated by institutional vs. foreign investors) on liquidity, finding that AT initiated by foreign investors plays a larger role in decreasing liquidity in the short term, while AT initiated by institutional investors has a more long term effect.

Keywords: algorithmic trading; liquidity; emerging markets; type of investors; market quality

1. INTRODUCTION

This research examined the effect of algorithmic trading (AT) in the Stock Exchange of Thailand on liquidity. AT is a type of trading determined by algorithms, which makes decisions and executes orders automatically. AT has increased around the world. The Stock Exchange of Thailand (SET) has many features that facilitate AT activities including Direct Market Access (DMA), Program Trading and

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[1,*]Pavinee Hassavayukul obtains a Master's degree in Electrical and Computer Engineering from Carnegie Mellon University (USA). She is a PhD candidate in the Department of Business Administration, National Institute of Development Administration, Thailand. Email: pavinee@gmail.com

Co-location Services. In 2011, program trading accounted for 3% of trading volume and 13.25% of the total number of trades (Likitapiwat, 2016). In 2015, the combined trading volume via DMA, and Program trading, accounted for 14% of trading volume (Stock Exchange of Thailand, 2015). At the time of writing, the number is expected to be around 20% although the exact number is not known due to the proprietary nature of the intraday data. Therefore, the rise of AT raises questions about its impact on market quality. Some researchers believe that an increase in automation in the stock market helps to improve liquidity as it should mitigate the liquidity provision and monitoring costs. However, others claim that the informational advantages of algorithmic traders may discourage slower traders from participation, causing overinvestment in AT technologies and intensifying systematic risk. As AT 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. Thus, empirical study is required to explore the aggregate impact of AT on liquidity. This paper contributes to financial and economic literature in two ways. Firstly, this study demonstrates how AT affects liquidity in an emerging market. Secondly, it introduces a method of identifying the AT proxies associated with each type of investor, and examines their respective effects on liquidity. The effects of AT on liquidity affect both

investors' welfare and the cost of capital for companies, as illiquidity represents costs to all types of investors. By holding less liquid stocks, investors require higher returns, which eventually leads to an increase in the cost of capital for firms and their stock values.

2. LITERATURE REVIEW

Literature in the field of AT is growing, yet empirical findings on the effect of AT on liquidity are still ambiguous and mostly focus on developed or fragmented markets. Therefore, empirical research in an emerging market is required.

- *Algorithmic Trading*

There are two main categories of AT: agency and proprietary algorithms (Menkveld, 2014). Agency algorithms are used by institutional investors such as in pension funds, brokerage firms and mutual funds to split large-sized orders to minimize the market impact, transaction costs and volatility risk (Almgren & Chriss, 2001). On the other hand, hedge funds, investment banks and proprietary trading firms use pre-programmed software to determine trading decisions. These types of traders use proprietary algorithms which include market-making and opportunistic trading (Hagströmer & Nordén, 2013). Opportunistic or speculative trading implements statistical arbitrage, directional trading and manipulation strategies (Aldridge, 2013). Hagströmer and Nordén (2013) showed that 71.5% of high frequency

trading (HFT) limit order submissions on the Nasdaq-OMX Stockholm exchange were involved in market maker strategy. They also found that the presence of market-making HFTs was higher when stocks had a larger market-cap, were less volatile, or had a higher trading volume and larger spread, which was contrary to the behavior of opportunistic HFTs. Due to different motivations, their impacts on liquidity are different.

- Liquidity

Illiquidity is generated due to market imperfections: participation costs, transaction costs, asymmetric information, imperfect competition, market microstructure, funding constraints and searching (Vayanos & Wang, 2012). Duffie (2010) discussed how search delays affected asset prices and liquidity. Automation and speed can lower trading frictions, i.e., information asymmetry, adverse selection problems, inventory risk, and order processing costs. AT can monitor markets more closely, adjusting orders accordingly. This enables investors to optimize their trade and therefore, their adverse selection risks are reduced, increasing securities liquidity (Carrion, 2013). Additionally, HFT's net positions at the end of each day are often zero, causing their inventory holding costs to reduce (Menkveld, 2013). HFT often trades a large amount of stocks. Therefore, their order processing costs are lower.

For high-latency traders, trading with low-latency traders causes them to be exposed to more adverse selection risks (Hagströmer & Nordén, 2013, Biais, Foucoult, & Moinas, 2015). The role of algorithmic traders in providing liquidity are non-binding, hence the liquidity they provide can be uncertain. Furthermore, liquidity may decline when the agency algorithms demand liquidity to execute their positions (Hasbrouck & Saar, 2013) or when HFT opportunistic arbitrageurs consume them. Hence, the impacts of AT on liquidity depend on the aggregate effects of various types of AT strategies.

Many researchers have reported the beneficial role of AT on liquidity. Foucault, Hombert, & Roşu (2016) provided a model mimicking traders' behavior upon the arrival of news and predicted that HFT enhances liquidity. Jovanovic & Menkveld (2016) modeled the role of HFT on the limit order book and showed that HFT reduces adverse selection. Hendershott & Riordan (2013) studied the effect of AT on the supply and demand of market liquidity for the Deutscher Aktien Index stocks and observed that when the bid-ask spreads were small, AT demanded liquidity and when the spreads were large, AT supplied liquidity. Zhang & Riordan (2011) documented similar results in the Nasdaq stocks. Carrion (2013) identified HFT accounts traded in NASDAQ based on the definitions of HFT, investigating their effects on market liquidity. It was found that HFT profited from market timing so when the spreads were wide, HFT

provided liquidity and when the spreads were narrow, HFT consumed liquidity. Using the same dataset, Hasbrouck & Saar (2013) introduced a new measurement for identifying HFT and measured liquidity. It was consequently shown that HFT reduced spreads while increasing order depth, both during normal and uncertain markets. Hendershott, Jones, & Menkveld (2011) investigated the impact of AT on liquidity on NYSE stocks in 2003, finding that AT caused an improvement in liquidity, reduction in adverse selection cost, and enhancement in price discovery. It also increased revenues for liquidity providers, though the effect was temporary. These effects were more profound in large-cap stocks. Brogaard, Hagströmer, Nordén, & Riordan (2015) examined the co-located traders, a subset of HFT. These traders could utilize information in order to reduce their adverse selection costs and thus helped to improve bid-ask spread and market depth.

On the multiple market study, Menkveld (2013) used trade and quote data from Chi-X and Euronext from 2007 to 2008 and found that HFT strategies helped to increase the trading activities and thus liquidity in Chi-X. This contributed to the success of Chi-X in the initial phase. Boehmer, Fong, & Wu (2018) found that AT ameliorated liquidity. In general, an increase in AT or HFT is mostly associated with a corresponding increase in liquidity. The result also prevails for other types

of securities. Viljoen, Westerholm, & Zheng (2014) provided the evidence that AT lowered effective spread, increased realized spreads and thus, reduced adverse selection risk in the SPI 200 futures. In foreign exchange markets, AT also advocated liquidity by providing it when needed and taking it away when the arbitrage opportunity arose (Chaboud, Chiquoine, Hjalmarsson, & Vega, 2014). Furthermore, this study affirmed that AT speeded up the price discovery process, while passing on adverse selection risks to high-latency traders. Malinova, Park, & Riordan (2018) also established the causal effect of the roles of HFT market makers in providing liquidity to the market and improving the welfare of slow traders. When the Deutsche Boerse exchange improved their infrastructure, the market latency for the Deutsche Boerse exchange was reduced from 50 to 10 milliseconds, facilitating AT. Riordan & Storkenmaier (2012) used this event as an instrumental variable and found that quoted spread was narrowed by 0.86 bps, enhancing liquidity through reducing adverse selection costs.

Conversely, some researchers have found that liquidity is worsened due to AT. Biais et. al. (2015) presented an equilibrium model of different latency traders, showing that the presence of fast institutional traders increases adverse selection for other slower traders. Bongaerts & Achter (2012) modeled the limit order book, revealing that the probability of orders submitted for execution by high-latency traders is reduced in the

presence of low-latency traders. Upon a reduction in latency from 10 to 1 seconds in NYSE's Hybrid market, Hendershott & Moulton (2011) discovered that quoted spreads were widened due to an increase in adverse selection cost (price impact). Van Ness, Van Ness & Watson (2015) examined the NASDAQ-listed and NYSE-listed stocks, showing that an increase in the cancellation rate of limit orders decreased liquidity in terms of effective spreads, realized spreads, depth, size of the limit order book, and price impact. Furthermore, Upson & Van Ness (2017) showed that algorithmic trading decreased the National Best Bid and Offer (NBBO) depth for NYSE stocks. Furthermore, Cartea, Payne, Penalva & Tapia (2019) showed that ultra-fast activity is related to larger quoted and effective spreads and lower depth on NASDAQ. A similar result prevailed in the experimental research conducted by Manahov (2016), who demonstrated that HFT imposes an adverse selection issue on informed investors who in return, require wider bid-ask spreads to compensate for this risk.

On the contrary, Ye, Yao, & Gai (2013) reported no relationship between liquidity and trading speed due to tick size restriction. Upon examining the role of institutional investors and HFTs in the FTSE250 index, Brogaard, Hendershott, Hunt, Latza, Pedace and Ysusu (2012) also found no relationship between AT and liquidity.

3. METHODOLOGY

3.1 RESEARCH PROBLEM AND QUESTIONS

The purpose of this research was to establish the relationship between AT and liquidity in the Stock Exchange of Thailand. Therefore, the research questions are: (i) does AT increase or decrease liquidity, (ii) is there a causal relationship between AT and liquidity, (iii) does AT initiated by institutional investors raise or lower liquidity, and finally (iv) does AT initiated by foreign investors improve or reduce liquidity.

3.2 HYPOTHESES

Based on the literature review, AT may increase or decrease liquidity. AT in the SET encompasses a small portion compared to the total trading volume and is executed by informed investors. For slower traders, trading with fast and informed investors may raise information asymmetry, causing an adverse selection problem and thus decreasing liquidity. Though automation by AT should increase liquidity by decreasing monitoring cost, due to its small distribution, its role in providing liquidity may be inadequate compared to its influence on other traders. Therefore, we hypothesize that:
$H1_a$: There is a negative relationship between AT and liquidity.
$H2_a$: There is a negative causal relationship between AT and liquidity.

H3$_a$: There is a negative relationship between AT initiated by institutional investors and liquidity.

H4$_a$: There is a negative relationship between AT initiated by foreign investors and liquidity.

3.3 SAMPLE AND DATA COLLECTION

We obtained the intraday order and deal data from the most recent data available from the SET Microstructure database, namely the 2016 data set. This data is proprietary data from the Stock Exchange of Thailand; therefore, one limitation of this study is the time period of the data used in the study. The SET100 stocks, or top 100 stocks in terms of average daily market capitalization, from March to December 2016 were selected for use in the study. The sample consisted of 20,400 observations taken over 204 trading days. The intraday order data consisted of information regarding the type of investor (retail, institutional or foreign), order side (buy or sell), order type, trade price, trade size and cancel time. The intraday deal data was composed of buyer and seller order times, trade price, trade size, and buyer and seller type. Data were time-stamped to the nearest millisecond. Stock specific data such as market capitalization and the total number of outstanding stocks were obtained from the Data Stream. Outliers were excluded, and data cleaning was performed.

3.4 ALGORITHMIC TRADING MEASUREMENT

There are two approaches to measuring AT, whereby the direct method involves identifying whether the transactions or trading behaviors are executed by ATs or not (Hagströmer & Nordén, 2013; Menkveld, 2013; Carrion, 2013), and the indirect method involves using total trading volume per traffic number as a proxy (Hendershott et al., 2011), or identifying linked messages that are executed by HFT using an order placement strategy which involves many submissions and cancellations (Hasbrouck & Saar, 2013).

Hendershott et al. (2011) proposed two methods of measuring AT activities, namely the number of electronic messages per minute, and the number of electronic messages per $100 of trading volume. In this study a normalized message traffic was used as a proxy as it better represents the amount of algorithmic trading activities, rather than just an increase in trading volume. Message traffic captures all order submissions, cancellations and trade reports. The rationale is that a rise in AT tremendously increases the message traffic. AT, especially HFT, increases the number of orders submitted to the market, while the ratio of orders executed to order submissions decreases. To avoid the effect of changes in trading volumes, the message traffic needed to be normalized. Therefore, the AT proxy was expressed as:

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

where AT_{it} is the 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.

The type of data used enabled the ability to distinguish the type of investors, specifically, retail, institutional and foreign investors. For this research, only the AT initiated by institutional and foreign investors was examined, as access to DMA was required to determine the mean for automatic submission of orders to the market. Thus the proxy for AT initiated by institutional investors was defined as:

$$AT\_I_{it} = -\frac{V\_I_{it}}{MT\_I_{it}}$$

while the proxy for AT initiated by foreign investors was defined as:

$$AT\_F_{it} = -\frac{V\_F_{it}}{MT\_F_{it}}$$

where AT_I_{it} and AT_F_{it} refer to the algorithmic trading, V_I_{it} and V_F_{it} refer to the trading volume in thousands of Baht, and MT_I_{it} and MT_F_{it} refer to the message traffic, regarding stock i on day t for the institutional and foreign investors respectively.

3.5 LIQUIDITY MEASUREMENT

Due to the data limitations of the SET database, which does not record price revisions, the limit order book could not be constructed correctly.

The following alternative measurements were consequently used.

3.5.1 Effective Half Spread (ESPREAD)

To overcome the limitations, the effective half spread was calculated using Roll's spread estimator. Roll's effective half spread is equal to:

$$ESPREAD_{it} = \frac{2\sqrt{-cov(\Delta P_{it}, \Delta P_{i,t-1})}}{\underline{P_{it}}} \; x \; 100$$

where $ESPREAD_{it}$ is the effective half spread and P_{it} is the price for stock i on day t. In this study, intraday trading prices were used for efficient estimation to avoid noise and due to the nonstationary nature of the data. The limitation of this measurement is that Roll's model assumes that the probability of price reversal is one-half (Roll, 1984).

3.5.2 Share Turnover (TURNOVER)

Share turnover is the ratio of the total amount of shares traded, to the average number of outstanding shares:

$$TURNOVER_{it} = \frac{NUM\_SHARE_{it}}{N_{it}}$$

where NUM_SHARE_{it} is the number of shares traded and N_{it} is the total number of outstanding shares for stock i on day t. It indicates the number of times stocks change hands. Therefore, the more liquid the stock is, the higher the share turnover is. It also represents the information

asymmetry level (Copeland & Galai 1983; Bartov & Bodnar, 1996).

3.5.3 Amihud's Illiquidity Estimate (ILLIQ)

Amihud (2002) measures illiquidity using the Amihud estimate (ILLIQ) which is defined as the average ratio of daily absolute stock returns, to the trading volume:

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

where R_{imd} is the stock return, and VOL_{imd} is the trading volume for stock i on day d of month m and D_{im} is the number of trading days for stock i on month m. This represents the daily price impact of order flow, or the absolute price change per baht of daily trading volume. In this study's data all values were recorded in Thai baht.

3.5.4 Liquidity Ratio (LR)

The liquidity ratio (LR) is the ratio of the total trading volume to the sum of the absolute value of the stock return:

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

where R_{imd} is the stock return, and 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 days for stock i on month m. The liquidity ratio measures market depth, as it associates trading volume with each

unit of change in the stock return (Amihud, Mendelson & Lauterbach, 1997). The higher the LR, the greater the liquidity or depth in the stock, as liquid stock can have a large amount of trading volume without prices being changed. This ratio is also related to the information asymmetry level.

3.6 MODEL SPECIFICATIONS

A panel data analysis was performed to test the null hypothesis: that there are no associations between AT and liquidity measures. To isolate the effect of AT on liquidity measures, the control variables employed were share turnover, stock volatility, inverse stock prices, and the logarithmic of market capitalization. The regression model used was:

$$LIQ_{it} = \alpha + \beta_1 AT_{it} + \delta' X_{it} + \mu_{it}$$

where LIQ_{it} encompasses the liquidity measures, i.e. effective half spread, share turnover, Amihud's illiquidity estimate and liquidity ratio, AT_{it} is the algorithmic trading proxy, and X_{it} is a vector of control variables, including realized volatility, the inverse of average price, the natural logarithmic value of market capitalization, and share turnover. For share turnover as a dependent variable, share turnover was deducted from the control variable vector.

The pooled OLS, the individual, time, and two-way fixed effects, as well as the individual and time random effects models were analyzed.

The two-way random effects model was excluded due to unbalanced data. A pooled OLS regression might confound the heterogeneity effects and its residuals might be correlated, leading standard errors to be biased. To address heterogeneity, fixed effects can be eliminated, by using fixed effects models, or by assuming the error terms as random variables using random effects models. To determine the appropriate model, an F-test was performed to choose between the pooled and fixed effects models, while the Hausman test was performed to select between the fixed effects and random effects models.

Additionally, to assure the causal relationship between AT and liquidity measures, we implemented the two-stage least squares estimation by finding the instrumental variable (IV_t). The SET has implemented computerized trading since 1991 and upgraded its system to "SET CONNECT" in 2012, boosting transaction speed and facilitating international trading activities. However, AT in the Stock Exchange of Thailand during this period was still premature. Therefore, using these two events as instrumental variables is not appropriate. Nonetheless, during October 2016, the market data exhibited the behavior of AT and the market experienced a flash crash. This was evidence of the participation of AT in the Stock Exchange of Thailand. As a result, it was presumed that AT was higher after October 2016 than in the earlier period. A dummy variable called "IV" was created, and

set to equal 1 after October 2016 and 0 before October 2016. The dummy variable "IV" did not correlate with liquidity, thus, the first stage regression became:

$$\widehat{AT}_{it} = \alpha + \beta_1 IV_{it} + \delta' X_{it} + \mu_{it}$$

In the second stage, the effect of AT on the liquidity model was shown using:

$$LIQ_{it} = \alpha + \beta_1 \widehat{AT}_{it} + \delta' X_{it} + \mu_{it}$$

As the aim was to investigate the relationship of AT initiated by each type of investor on liquidity measures, AT initiated by institutional investors, AT initiated by foreign investors, and their interaction terms was incorporated into the regression models. The interaction term enables understanding of the relationship for AT initiated by each type of investor. Consequently, the following multivariate models were implemented:

$$LIQ_{it} = \alpha + \beta_1 AT\_I_{it} + \beta_2 AT\_F_{it}$$
$$+\beta_3 AT\_I_{it} x AT\_F_{it} + \delta' X_{it} + \mu_{it}$$

where AT_I_{it} and AT_F_{it} were the AT initiated by institutional and foreign investors respectively.

4. RESULTS AND DISCUSSION

- Descriptive statistics

The descriptive statistics are presented in Table 1. For daily variables, effective half spread and share turnover had an average of

0.27% and 0.0062 respectively. AT averaged at -40.58 while AT initiated from institutional investors had an average of -89.26 and AT initiated from foreign investors had an average of -39.01. Lastly, the average realized volatility was 0.26%.

Regarding monthly variables, mean values of Amihud's illiquidity estimate, liquidity ratio, and share turnover were 0.0178, 320.09 and 0.1307 respectively. The algorithmic trading proxies had an average value of -42.50 when combining data from all investor types, -91.91 for institutional investors, and -38.29 for foreign investors. The monthly realized volatility averaged 1.93%.

Table 1 - Summary Statistics of Variables

Variables	Mean	Median	Std. Dev.	Min.	Max.
Daily					
Effective half spread (%)	0.27	0.25	0.13	0.00	0.95
Share turnover	0.0062	0.0026	0.0216	0.00002	0.5389
AT (all)	-40.58	-30.01	34.43	-248.41	-1.04
AT (institutional)	-89.26	-64.53	82.54	-614.43	-0.01
AT (foreign)	-39.01	-23.30	44.06	-459.70	-0.01
Realized volatility (%)	0.26	0.24	0.13	0.00	4.92
Monthly					
Amihud's illiquidity	0.0178	0.0100	0.0246	0.0004	0.1950
Liquidity ratio	320.09	122.41	468.78	6.47	3,387.12
Share turnover	0.1307	0.0634	0.4051	0.0056	6.8949
AT (all)	-42.50	-33.37	31.29	-174.44	-6.73
AT (institutional)	-91.91	-72.43	71.03	-425.39	-1.14
AT (foreign)	-38.29	-25.36	35.36	-172.08	-0.99
Realized volatility (%)	1.93	1.79	0.86	0.29	11.60
Stock characteristics					
Market capitalization (billion THB)	108.58	47.03	162.69	6.07	1,048.20
The inverse of share price (1/Baht)	0.1028	0.0478	0.1326	0.0019	0.6824

The correlation analysis showed that effective half spread and Amihud's illiquidity estimate were positively correlated with all types of algorithmic trading proxies, as seen in Table 2 (p-value < 0.01). Share turnover and the liquidity ratio were negatively correlated with all types of algorithmic trading proxies (p-value < 0.01).

- Regression analysis

Multivariable regressions were conducted using pooled OLS, fixed effects and random effects. The F-test between the pooled OLS and fixed effect models rejected the null hypotheses, confirming that there were fixed effects. The selection test used between fixed and random effects models was the Hausman test. To avoid confounding effects, both cross-sectional and time-series variations were analysed. As a result, the two-way fixed effects model was adopted as the most appropriate model as there was both individual and time heterogeneity. Therefore, the model used became:

$$\overline{LIQ_{it}} = \beta_1 \overline{AT_{it}} + \delta' \overline{X_{it}} + \mu_{it}$$

where $\overline{LIQ_{it}}$, $\overline{AT_{it}}$ and $\overline{X_{it}}$ were the mean values for the corresponding variables.

Table 3 outlines the coefficient estimates of the pooled OLS and the two-way fixed effects regression. The coefficients from the pooled OLS model are significant for effective spread, share turnover and liquidity ratio. Thus, the null hypotheses were rejected for these models. There is no significant relationship between Amihud's illiquidity estimate and AT. The regression results from the two-way fixed effects models showed that all four liquidity measures exhibited statistically significant relationships with AT and yielded four outcomes.

Table 2 – Correlation analysis.

Variables	Effective half spread	Share turnover	Liquidity ratio	Amihud's illiquidity
AT (all)	0.3183[***]	-0.1154[***]	-0.8674[***]	0.4618[***]
AT (institutional)	0.2570[***]	-0.1528[***]	-0.8852[***]	0.4848[***]
AT (foreign)	0.2620[***]	-0.1987[***]	-0.8910[***]	0.4551[***]

[*], [**] and [***] denote significance at the 10%, 5% and 1% level.

Table 3 – Regression analysis.

Variables	Effective half spread (t-statistic)	Share turnover (t-statistic)	Liquidity ratio (t-statistic)	Amihud's illiquidity (t-statistic)
	Pooled OLS			
Intercept	0.0036 (0.22)	0.0115*** (3.92)	-1193.1247*** (-8.66)	0.2605*** (10.08)
AT	0.0014*** (38.23)	-0.0001*** (-19.68)	-11.3004*** (-33.60)	2.2661×10^{-7} (0.00)
Volatility	18.40*** (26.27)	2.0535*** (16.42)	-80.8517*** (-9.79)	-0.0033*** (-2.11)
1/price	0.1306*** (19.15)	0.0126*** (10.33)	323.3061*** (6.30)	-0.0288*** (-2.99)
ln(market_cap)	0.0185*** (16.03)	-0.0012*** (-5.76)	80.4751*** (8.10)	-0.0162*** (-8.70)
Turnover	0.0337 (0.84)		82.1615*** (16.84)	-0.0059* (-1.87)
Adjusted R-squared	14.88%	4.15%	81.79%	16.24%
	Two-way fixed effects			
AT	0.0011*** (27.00)	-0.0002*** (-29.51)	-8.0796*** (-17.07)	0.0002*** (5.17)
Volatility	13.4997*** (17.64)	1.9719*** (18.06)	-73.51*** (-8.50)	-0.0011 (-1.35)
1/price	0.0466 (1.05)	-0.0171*** (-2.66)	806.24*** (2.62)	0.2231*** (7.36)
ln(market_cap)			-783,008.24 (-0.06)	480.84 (0.42)
Turnover	-0.4348*** (-8.64)		168.59*** (6.34)	0.0005 (0.21)
Adjusted R-squared	3.99%	5.90%	21.18%	0.88%

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

First, the coefficient of AT on effective half spread is 0.0011 (p-value < 0.01). As one standard deviation in AT is equal to 34.43, a one standard deviation change in AT results in a 0.0011 x 34.43 = 0.038% change in effective half spread, which is equivalent to 14% change in effective half spread from the average. Therefore, an increase in AT is associated with wider effective half spread. This result is contrary to the

result from Hendershott et al. (2011) in which AT decreased bid-ask spread.

Second, the share turnover displayed a negative relationship with AT. Share turnover decreased by 0.0034 units or 56% from its average value in response to an increase of one standard deviation in AT. Compared with prior research (Hendershott et al., 2011), the direction of the share turnover coefficient is in line with previously determined coefficients, showing a negative relationship.

Third, the liquidity ratio model reveals that AT has a reverse relationship with the liquidity ratio. For each additional standard deviation in AT, the liquidity ratio declined by 8.0796 x 31.29 = 252.81 units or 79% from the mean value. Clearly, AT distorts liquidity.

Finally, the Amihud's illiquidity estimate increases as AT rises. When AT accumulates by one standard deviation, Amihud's illiquidity estimate also increases incrementally by 0.0063 units or 35.2% from the average Amihud's illiquidity estimate. This is consistent with results of earlier research, and shows that AT deters liquidity.

- Two-stage least squares (2SLS) estimation

To establish the causal relationship and alleviate endogeneity, the models were estimated using the 2SLS analysis. Table 4 reports the regression results. In the first stage, the instrumental variable (IV) was regressed on AT.

Using OLS, a significant relationship was shown between AT and IV (p-value < 0.01). The correlation between IV and liquidity was also examined to check for endogeneity and found no relationship, confirming the validity of IV. Second-stage regressions asserted that there is a positive relationship between AT and effective half spread (p-value < 0.01), and a negative relationship between AT and share turnover (p-value < 0.05), consistent with previous research. However, the magnitudes found in this model are larger than those of fixed effects models. The coefficients of effective half spread, and share turnover are 0.0026 and -0.0003 respectively. When AT is enhanced by one standard deviation, effective half spread decreases by 33.2% from its mean value. Similarly, share turnover falls by 166.6% from the mean value in response to each standard deviation increase in AT. Therefore, it is concluded that a higher level of AT causes wider spread and a lower share turnover, leading to reduced liquidity.

- AT initiated by each type of investor, and liquidity

Assessing the effect of AT used by each type of investor on liquidity, by a two-way fixed effect model reveals that AT associated with both institutional and foreign investors is related to reduced effective spread, lower share turnover, and higher levels of illiquidity as depicted in Table 5. For the liquidity ratio, it was found that only AT initiated by

Table 4 – 2SLS analysis.

Variables	First Stage (AT)	Second Stage (Effective Half Spread)	First Stage (AT)	Second Stage (Share Turnover)
Intercept	276.01*** (105.16)	-0.3470 (-1.38)	279.64*** (105.77)	0.0621 (1.44)
IV	2.3787*** (5.68)		2.50*** (5.90)	
AT		0.0026*** (2.91)		-0.0003** (-1.99)
Volatility	-2,652.84*** (-18.95)	21.84*** (8.52)	-3,029.89*** (-21.64)	1.4936*** (3.04)
1/price	20.78*** (15.24)	0.1043*** (5.20)	19.18*** (13.96)	0.0161*** (5.05))
ln(market _cap)	-21.86*** (-128.23)	0.0462** (2.33)	-22.11 (-128.74)	-0.0052 (-1.53)
Turnover	-155.88*** (-19.61)	0.2318 (1.57)		

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

institutional investors plays a role in decreasing the liquidity ratio, while AT initiated by foreign investors showed no relationship with the liquidity ratio.

AT initiated by institutional and foreign investors was linked to 9.17% and 14.69% respective decreases in effective spread from the mean value. Similarly, the interaction between AT initiated by each type of investor led to a wider effective half spread of approximately 3%. Likewise, an increase of one standard deviation in AT initiated by institutional and foreign investors diminished share turnover by 41.24% and 71.06% respectively, while the interaction between each type of AT resulted in lowering share turnover by 6.6%.

Amihud's illiquidity estimate rose by 79.8% and 59.6% from its mean value due to each standard deviation increase in the AT associated with institutional and foreign investors respectively. The interaction between the AT caused by institutional and foreign investors increased Amihud's illiquidity estimate by 24.5% from the average. Similarly, when AT associated with institutional investors rises by one standard deviation, the liquidity ratio receded by 16.8%. Interestingly, the sign of the coefficient of the interaction term is opposite, asserting that the interaction between the two types of AT initiated by different types of investors improves the liquidity ratio by 14.2%.

Table 5 - Regression for AT initiated by institutional and foreign investors on liquidity.

Variables	Effective half spread (t-statistic)	Share turnover (t-statistic)	Liquidity ratio (t-statistic)	Amihud's illiquidity (t-statistic)
AT_I	0.0003***	-3.0981x10⁻⁵***	-0.7572***	0.0002***
	(17.57)	(-9.27)	(-2.84)	(6.66)
AT_F	0.0009***	-0.0001***	-0.8781	0.0003***
	(21.96)	(-19.60)	(-1.36)	(5.13)
AT_IxAT_F	2.3356x10⁻⁶***	-1.1269x10⁻⁷***	0.0181***	1.7336x10⁻⁶***
	(15.97)	(-4.38)	(7.00)	(6.99)
Volatility	13.4343***	2.0300***	-59.62***	-0.0008
	(17.43)	(15.06)	(-7.03)	(-0.96)
1/price	0.0258	-0.0247***	90.49	0.1838***
	(0.57)	(-3.12)	(0.28)	(6.04)
ln(market_cap)			-4,436,315	553.37
			(-0.38)	(0.49)
Turnover	-0.2993***		138.37***	0.0002
	(-7.23)		(5.23)	(0.08)
Adjusted R-squared	4.26%	6.14%	26.81%	5.09%

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

The results show that AT initiated by foreign investors has more profound effects on undermining liquidity in terms of effective half spread and share turnover, whereas AT initiated by institutional investors plays a larger role in distorting liquidity in terms of Amihud's illiquidity estimate and liquidity ratio. The interaction between AT initiated by each type of investor also augments the effect, except for the case of liquidity ratio.

- Discussion

In summary, the results indicate that increases in AT deteriorate liquidity. This result is contradictory to those of Hendershott et al., 2011, which showed that an increase in competition among AT increases market liquidity. However, it confirms the results shown by Hendershott & Moulton (2011), Van Ness et al. (2015), Upson & Van Ness (2017), Cartea et al. (2019) and Manahov (2016). As share turnover is inversely related to information asymmetry, a decline in share turnover may reflect the rise in information asymmetry. Therefore, increases in AT are related to increases in information asymmetry. There are two hypotheses to explain

this result. The first explanation is the informed limit order book hypothesis, which indicates that when information asymmetry is high, informed investors will submit and cancel limit orders in the limit order book. This causes price volatility to be high. In response to this, liquidity providers withdraw from the market (Goettler, Parlour & Rajan, 2009). Therefore, an increase in message traffic, signals higher information asymmetry and leads to lower liquidity provisions. On the other hand, according to the AT adverse selection risk hypothesis, an increase in AT increases adverse selection risks, causing market liquidity to decrease. As adverse selection cost is one of the determinants of bid-ask spread, an increase in AT may widen bid-ask spread as a form of compensation for high latency traders when trading with algorithmic traders. Consequently, as other types of investors are reluctant to trade, the price impact becomes higher leading to an increase in Amihud's illiquidity estimate due to an increase in AT. Furthermore, as the liquidity ratio is associated with depth, the negative relationship contends that a rise in AT lowers depth and results in higher changes in stock returns, inferring that less orders are available at certain price levels reflecting a lower participation rate.

Additionally, the results of this study provide evidence that AT initiated by foreign investors contributes more in reducing liquidity in the short run. This is because trading with foreign investors, who represent more informed investors,

may exacerbate information asymmetry, consistent with the results from Kim and Yi (2015) in the Korean market and Seasholes (2004) in Korean, Taiwanese and Thai markets. These researchers claimed that foreign investors possess informational advantages and hence are more informed investors than institutional investors. As a result, the AT initiated by foreign investors has a greater impact on worsening liquidity by increasing information asymmetry.

5. CONCLUSION

Algorithmic trading has gained importance in the stock market around the world. Its effect on liquidity is still being debated. This paper aims to establish the impact of AT on liquidity in the Stock Exchange of Thailand using various methods to cope with endogeneity issues. The research has shown that an increase in AT is associated with wider effective half spread, decreased share turnover, increased Amihud's illiquidity estimate, and a lower liquidity ratio. Therefore, AT deteriorates liquidity. It establishes a causal relationship using 2SLS regression and ascertains that AT causes the effective spread to enlarge, and share turnover to decline. Computing AT proxy by types of investors, it was found that AT initiated by institutional and foreign investors enlarges effective half spread, decreases share turnover, escalates Amihud's illiquidity level and lowers the liquidity ratio. AT initiated by foreign investors plays a greater role in widening effective half

spread and reducing share turnover, which are the liquidity measures on the daily horizon. In contrast, AT initiated by institutional investors plays a greater role in increasing Amihud's illiquidity estimate and decreasing the liquidity ratio, which are the liquidity measures on the monthly horizon. Information asymmetry was used to explain the phenomena that participation of algorithmic traders increases information asymmetry in the market, preventing other investors from trading and hence, distorting liquidity.

The impact of each type of AT on liquidity has important implications for regulators to ensure healthy market conditions for all types of investors. Future studies can be conducted on identifying the hypothesis between the informed LOB hypothesis and the AT adverse selection risk hypothesis, which can explain a decrease in liquidity due to an increase in AT.

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