Does algorithmic trading improve liquidity around dividend announcement?Evidence from the Stock Exchange of Thailand.

Miss Chotika Chatchawanwanit

An Independent Study Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Finance
Department of Banking and Finance
FACULTY OF COMMERCE AND ACCOUNTANCY
Chulalongkorn University
Academic Year 2020

น.ส. โชติกา ชัชวาลวานิช

สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาการเงิน ภาควิชาการธนาคารและการเงิน
คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2563

Independent Study Title	
By	Miss Chotika Chatchawanwanit
Field of Study	Finance
Thesis Advisor	Assistant Professor TANAKORN LIKITAPIWAT, Ph.D.

Accepted by the FACULTY OF COMMERCE AND ACCOUNTANCY, Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of Science

INDEPENDENT STUDY COMMITTEE

.... Chairman
()

.... Advisor
(Assistant Professor TANAKORN LIKITAPIWAT, Ph.D.)

.... Examiner
(Assistant Professor SIRA SUCHINTABANDID, Ph.D.)

.... Examiner
(TANAWIT SAE SUE, Ph.D.)

สาขาวิชา	การเงิน	ลายมือชื่อนิสิต ....
ปีการศึกษา	2563	ลายมือชื่อ อ.ที่ปรึกษาหลัก ....

6181886826 : MAJOR FINANCE
KEYWOR D: algorithmic trading

Chotika Chatchawanwanit : Does algorithmic trading improve liquidity around dividend announcement?Evidence from the Stock Exchange of Thailand.. Advisor: Asst. Prof. TANAKORN LIKITAPIWAT, Ph.D.

This study investigates the impact of the entry of algorithmic trading on Thailand's stock market liquidity around dividend announcement during 2001 – 2016. We find some evidence to support that the entry of algorithmic trading in Thai stock market and their increase activities in the market help to provide more liquidity in term of trade volume in stock market liquidity especially after the dividend announcement releases. However, the rise of algorithmic trading tend to lead the market participants to consume liquidity in term of market depth at both best bid and bet offer rather than providing the standing orders in the market during period of high information asymmetry.

Field of Study:	Finance	Student's Signature ....
Academic Year:	2020	Advisor's Signature ....

ACKNOWLEDGEMENTS

I would like to express my special thanks of gratitude to my advisor (Ajarn. Tanakorn Likitapiwat) who gave me the opportunity and fruitful guidance to do this project , which also helped me in doing a lot of Research and i came to know about so many new things.

Lastly, I would also like to thank my family and friends for their big support and always understand and provide fruitful inspiration to be to make this accomplishment.

Chotika Chatchawanwanit

TABLE OF CONTENTS

Page

1. Introduction

The algorithmic trading on the Stock Exchange of Thailand has allowed trading software that can automatically submit orders into the market since 2007. This change has revolutionized the way of trading financial assets and the arrival of algorithmic trading dramatically reduces the costs incurred by intermediaries, costs of trading, improve liquidity and enable more efficient risk sharing (**Hendershott et al., 2011)**. Each market participants have their own algorithms trading in the market being as a liquidity supplier or liquidity demanders and also have an advantage on fast automated trading technology. Thus, algorithms react faster and more correctly to any announcements than non-algorithmic traders due to better in timing their trade and their trading also accelerates the information incorporate process (**Frino et al., 2017**).

In the traditional financial economics view, the public information is reflected in price before anyone is able to trade on it (i.e. **French and Roll, 1986**). **Grossman and Stiglitz (1980),** on the other hand, propose that there is a partially price reflect the information of informed investors. Easley and O'Hara (1992) suggest that both public and private information accumulate overnight and thus the information asymmetry will be highest before the open. Barclay and Hendershott (2003) also propose that the information asymmetry is high before the market open and most trades are more likely to be informed that give the preopen more price discovery than at any other time of the day. Thus, once dividend announcement releases are available to trade, algorithmic trading as a faster decision making may be able to exploit any mispricing due to the delayed reaction to new arrival information within first minutes. Moreover, with the fast-automated trading technology, they have an advantage in speed execution and rapidly react to any market condition changes, so they will be better in managing their risk exposure and costs of trading.

While some previous literatures study the relationship between algorithmic trading and market liquidity, no prior study has been study the relationship between algorithmic trading and market liquidity around dividend announcements and most of their sample dataset obtained from the exchange that using quote driven market i.e. NASDAQ and LSE unlike the Stock of Exchange of Thailand that we has been using order driven market type. The Stock Exchange of Thailand (SET)'s type is an order driven market which buyers and sellers submit their own prices and quantity that are willing to buy or sell a particular security. The order execution is usually prioritized based on price and then time. In other countries, some dividend announcements release during continuous trading hours, and thus prior literatures focus only on the market reaction around dividend announcements. Therefore, in our study, we would like to examine the relationship between algorithmic trading and market liquidity between last -30 minutes in last market trading session before dividend announcement and first +30 minutes in first market open session after each dividend announcement because dividend announcements in Thailand are released during either after market close or intermission trading time.

Our objective, in this paper, aims to examine whether the market liquidity during the first market trading session available after dividend announcements, the period of having probability of high information asymmetry, will be improved in the presence of algorithmic trading based on financial economic theoretical studies. The traditional theories argue that information asymmetry increases after public new announcements and uninformed traders may hesitate to trade against informed investors resulted in a decrease in market liquidity. However, the entry of algorithmic trading may help to increase market liquidity due to the advantage of speed execution and the ability of detecting informed traders' pattern.

It is an important issue that regulators and policymakers should be keenly interested in it in order to improve market quality to be fair and transparent. Thus, this paper may contribute useful information to both regulators and the stock market of Thailand. If the presence of algorithmic trading does improve the market liquidity, they should provide greater facility to attract even more algorithmic trading both domestic and international traders.

2. Literature review

There are several previous literatures that have been documented about stock market liquidity, information asymmetry around the new upcoming public announcements and the impact of an arrival of algorithmic trading on market liquidity as follows.

2.1 Literature review of information asymmetry around public new announcements

A common belief is that public news announcements reduce heterogeneity of information across investors (**Glosten and Milgrom 1985**). The public new information is reflected in price before anyone can trade on it (i.e. **French and Roll, 1986**), thus after the new announcement, the information asymmetry will decrease between informed investors and uninformed investors. **Grossman and Stiglitz (1980),** on the other hand, propose that there is a partially price reflect the information of informed investors. **Kim and Verrecchia (1994)** also presume that new releases increase heterogeneity of information because informed investors have an advantage interpreting newly released information.

There are some several prior studies which their findings show the increase in information asymmetry after public new announcements which are consistent with **Kim and Verrecchia (1994)**. **Venkatesh and Chiang (1986)** examine changes in bid and ask spreads around both dividend and earning announcements and find wider spreads around the announcements. **Krinsky and Lee (1996)** find that the adverse selection increases in anticipation of upcoming earnings announcements and increases even further after the announcements. **Lee, Mucklow, and Ready (1993)** also find that market makers widen spreads and reduce market depth in anticipation of upcoming earnings announcements.

In traditional studies, there are two classes of traders: uninformed liquidity traders and informed traders (e.g., **Glosten and Milgrom 1985**). Both may know the timing of anticipated dividend announcements, but informed investors may know something about their contents while uninformed investors do not. Thus, informed investors may trade on their private information that allows them to profit from uninformed investors i.e. liquidity traders and market makers. Consequently, uninformed investors may hesitant to trade in the situations in which it is more likely that informed investors have valuable private information prior to the public new information, with the intent of profitably trading on this superior information and has higher probability of trading against informed traders resulted in a decrease in market liquidity (**Easley and O'Hara, 1992**). The decrease in market liquidity may be caused by uninformed investors who need to limit the amount of risk they face from the increase of adverse selection costs. **Foster and Viswanathan (1990)** show that uninformed traders have incentives to maximize their likelihood that their trades are trading with other uninformed traders.

Once the public new announcement releases during either after market close period or intermission trading time, the public new information is not able to immediately reflect to the stock price but will accumulate until the market first available to trade resulted in an increase in information asymmetry in around market open. **Easley and O'Hara (1992)** suggest that both public and private information accumulate overnight and thus the information asymmetry will be highest before the open. **Barclay and Hendershott (2003)** propose that the information asymmetry is high before the market open and most trades are more likely to be informed that give the preopen more price discovery than at any other time of the day.

2.2 Literature review of stock market liquidity and information asymmetry

The term of liquidity has been widely known among academics and practitioners to typically describe (1) tightness (the cost of turning around the position over a short period of time), (2) depth (the size of an order flow innovation required to change prices a given amount), and (3) resiliency (the speed with prices recover from an uninformative shock) **(Kyle, 1985). Black (1971)** suggests that stock market has liquidity if following condition hold: (1) bid and ask prices are always available for investor to buy and sell small amount of stock immediately, (2) the spreads is always small, (3) an investor who is buying or selling a large amount of stock, in absence of special information, can expect to do over a long period of time at price not very different, and (4) an investor can buy or sell a large block of stock immediately. Those bid and ask spreads, in some prior studies, involve the issue of the adverse selection while investing in information asymmetry companies. **Ascioglu and al. (2007)** presumes that the bid and ask spreads exacerbate and liquidity decreases in case of information asymmetry. Liquidity supplier's standing orders provide free trading option to other traders **(Copeland and Galai, 1983). Foucault et al. (2003)** study the equilibrium level of effort that liquidity suppliers should spend monitoring cost to reduce this option's cost. This cost involves the adverse selection cost of being picked off on liquidity suppliers. If some traders are better at avoiding being picked off, they can impose adverse selection costs on other liquidity suppliers, and thus drive out other liquidity suppliers from the stock market **(Rock, 1990).**

Glosten and Milgrom (1985) and **Kyle (1985)** have found that information asymmetry is negatively related to liquidity as measured by the bid and ask spreads and by Kyle's lambda (price impact). **Heflin et al. (2001)** presume that higher quality disclosures are associated with reduced risk of informed trading and hence increased stock market liquidity. In sum, in several previous literatures, there is a relationship between stock market liquidity and information asymmetry presuming that the liquidity will decrease when the information asymmetry seems to be higher in the stock market. This is because of the adverse selection cost of being picked off that liquidity suppliers have to face.

2.3 Literature review of the impact of algorithmic trading on market liquidity

The rise of algorithmic trades has obvious direct impacts to the stock market i.e. the intense trading activities submitted by algorithmic automated trading system threatens to overwhelm exchanges. However, the arrival of algorithmic trades may help to enhance market liquidity. **Hendershott et al. (2011)** shows that algorithmic trades enhance market liquidity significantly particularly for large stocks by finding that quoted and effective spreads narrow which are a result of a decrease in adverse selection. **Aggarwal and Thomas (2017)** suggests that algorithmic trading improves market quality by reducing transactions costs, improving depth, decreasing intraday price volatility and liquidity risk, and reducing the incidence of extreme price movements. This paper evidence, however, contrary to the existing literature by indicating that algorithmic trading significantly beneficial for small stocks.

Algorithmic trading has an advantage of having fast-automated trading technology to respond to new arrivals of information quickly and in the correct direction with regard to the impact of new on price. Some common techniques that algorithmic trading strategies may use are processing to read and interpret upcoming news text automatically and trigger theirs trading strategies based on market condition changes which its market condition may, at that time, based on action from informed traders during period of high information asymmetry. **Hendershott and Riordan (2011)** assume that high frequency trading, one type of algorithmic trading, could predict price changes over short horizons of less than 30 seconds and their marketable order's informational advantage is sufficient to overcome the bid and ask spreads and trading fees to generate positive trading revenues (**Brogaard, Hendershott and Riordan, 2014**). Moreover, the direction of high frequency trading is correlated with public information, such as macro news announcements, and market-wide price movements.

3. Hypotheses

There are two main types of traders during public new announcement period: uninformed investors vs informed investors which informed investors typically tend to have valuable private information over uninformed investors. Most of dividend announcements are known ex ante event, where investors can anticipate the upcoming announcements. Informed investors, however, may have valuable private information around the dividend announcements over the uninformed investors and tend to trade on their superior information. Consequently, uninformed investors (i.e. liquidity traders and market makers) may face greater adverse selection costs around dividend announcements, which subsequently decrease their exposures to limit the amount of risk from trading against informed traders resulted in a decrease in market liquidity. Consistent with **Kim and Verrecchia (1994)** who presume that information asymmetry should be high, and liquidity accordingly low, after the new event due to the interpretation advantage of the informed investors is greater.

Recall, **Hendershott et al. (2011)** proposes that the rise of algorithmic trading helps to improve market liquidity, reduce cost of trading and enable more efficient risk sharing. Moreover, the advantage of automated technology also helps to speed up the trade execution and thus rapidly react to market condition adjustment. Consequently, they tend to be better in managing their risks and able to reduce cost of adverse selection during this high information asymmetry period. Consistent with **Frino et al. (2017)** who presume that the algorithmic traders react faster and more correctly to any new announcements than non-algorithmic traders due to better in timing their trade and their trading, moreover, also accelerates the information incorporate process.

In sum, as high information asymmetry is high after dividend announcement release **(Kim and Verrecchia, 1994)**, we should observe liquidity accordingly low in the first available market trading session after dividend announcement releases in pre-algorithmic trading period while we should observe an improvement, or higher, in market liquidity after dividend announcement releases in post-algorithmic trading period. This leads to our hypothesis in order to examine the impact of algorithmic trading on market liquidity around dividend announcements in the stock market of Thailand.

H1: Algorithmic trading has a positive relation to market liquidity surrounding dividend announcement.

H2: Market liquidity is higher in post-algorithmic trading period than pre-algorithmic trading period.

H2.1 Trading volumes are higher in post-algorithmic trading period than pre-algorithmic trading period.

H2.2 Market depth is higher in post-algorithmic trading period than pre-algorithmic trading period.

4. Data and Methodology

4.1 Sample Data

Our analysis considers component securities of SET index extracting unique dataset from the Stock Exchange of Thailand for the period January 1, 2001 to December 30, 2016. The data of dividend announcements' date obtains from SETSMART database that provide information of date of dividend announcements. The dividend announcements include all type of announcements (quarterly, semi-annual, annually and interim dividend). We will separate this testing into two periods in order to examine the impact of algorithmic trading around dividend announcements: pre-algorithmic trading (before 2007) and post-algorithmic trading (after 2007). We will select those companies that are trading in the stock market during 2001 to 2016 and also pay the dividend at least one time in pre-algorithmic trading and one time in post-algorithmic trading period. Thus, any companies start to pay dividend after 2007 will be drop and also those companies that do not exist in the stock market for entire the period of 2001-2016 will be dropped. **Table 1** summarizes the results of our sample data selection process. Our final sample of 960 announcements is split into 369 announcements during pre-algorithmic trading period and 591 announcements during post-algorithmic trading period.

Table 1

Dividend announcements sample and selection process across sample period during January 2001 - December 2016
This table summarizes the selection process used to identify the final sample of dividend announcements. The final sample obtains from Setsmart database that provides market data surrounding dividend announcements in both pre-algorithmic trading and post-algorithmic trading period. The sample includes 63 stocks that are listed in SET Index during 2001-2016 and also pay the dividend at least one time in pre-algorithmic trading and one time in post-algorithmic trading period.

Dividend Announcements Sample	**All Period**	**Pre-Algorithmic**	**Post-Algorithmic**
Total dividend announcements in after hour period	759	279	480
Total dividend announcements in intermission period	201	90	111
Final sample	960	369	591

4.2 Proxies for Algorithmic Trading

To investigate the impact of algorithmic trading on market liquidity around dividend announcements, we determine the change in algorithmic trading via several proxies which are typically used in prior literatures (**Hendershott et al., 2011**): (1) Message Traffics per minute (2) Algo_trade

First, we identify message traffic as the total amount of trades per minute includes order submissions, modification and cancellations requests in the order book for each stock in SET on a given trading days via new records at each timestamp, which is consistent with Hendershott et al. (2011). Lastly, as we cannot observe a particular order submitted to the exchange whether it is generated by algorithmic trading system, we follows Hendershott et al. (2011) by using the rate of electronic message traffic to be proxy for the amount of orders generated by algorithmic trading. The message traffic also includes order submissions, modification and cancellations requests. Then, we will normalize the raw message traffic over time in order to measure the change in the nature of trading otherwise this measure will also capture the increase in amount of trading over time.

$$Algo\_trade_{it} = \frac{-THB\,Volume_{it}/\,100}{Message\,Traffic_{it}}$$

Algo_tradeit defined as the negative of trading volume (in hundreds of THB) divided by message traffics.

Figure 1 and Figure 2 show the evolution of (1) Message Traffics per minute and (2) Algo trade sequentially from January 2001 to December 2016 for symbols in SET Index that released dividend announcements. Out algorithmic trading proxies do not appear immediately around the introduction of algorithmic trading period in 2007. This might be because of learning effect and thus take some time for algorithmic trading to enter to the stock market with fully capacity.

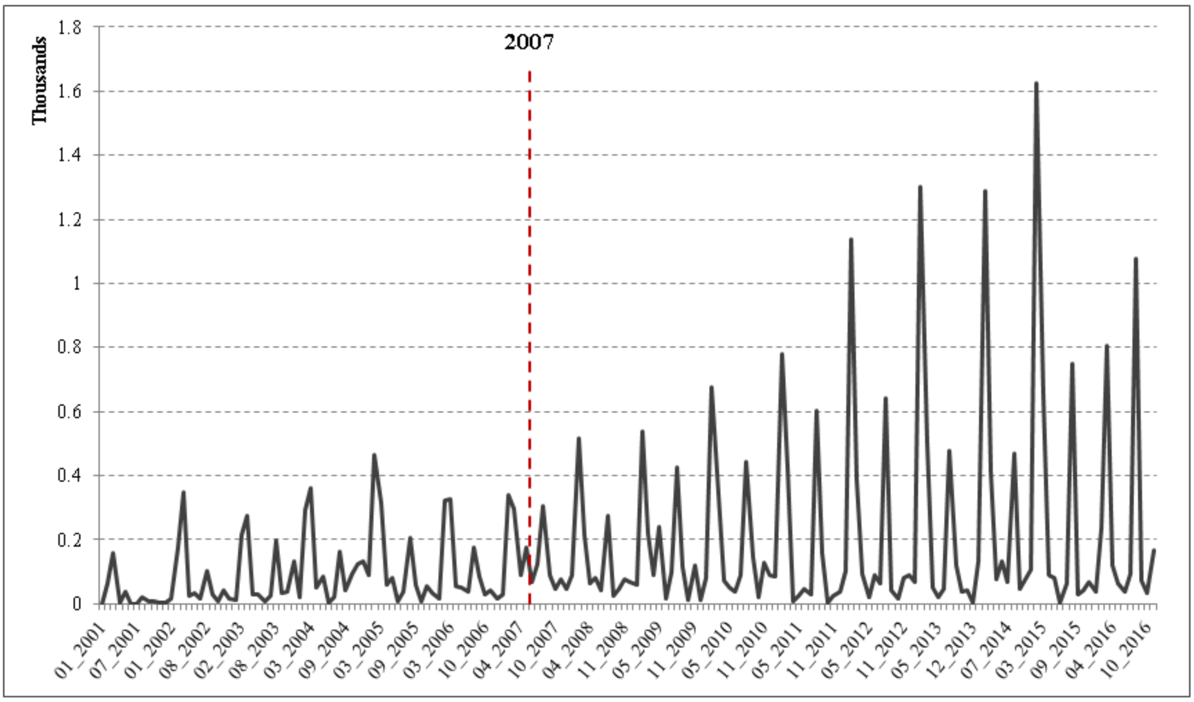


Figure 1. Algorithmic trading measures. This figure depicts the algorithmic trading proxy "Message Traffic per 1-minute interval" on daily basis and highlights the arrival of algorithmic trading in 2007.

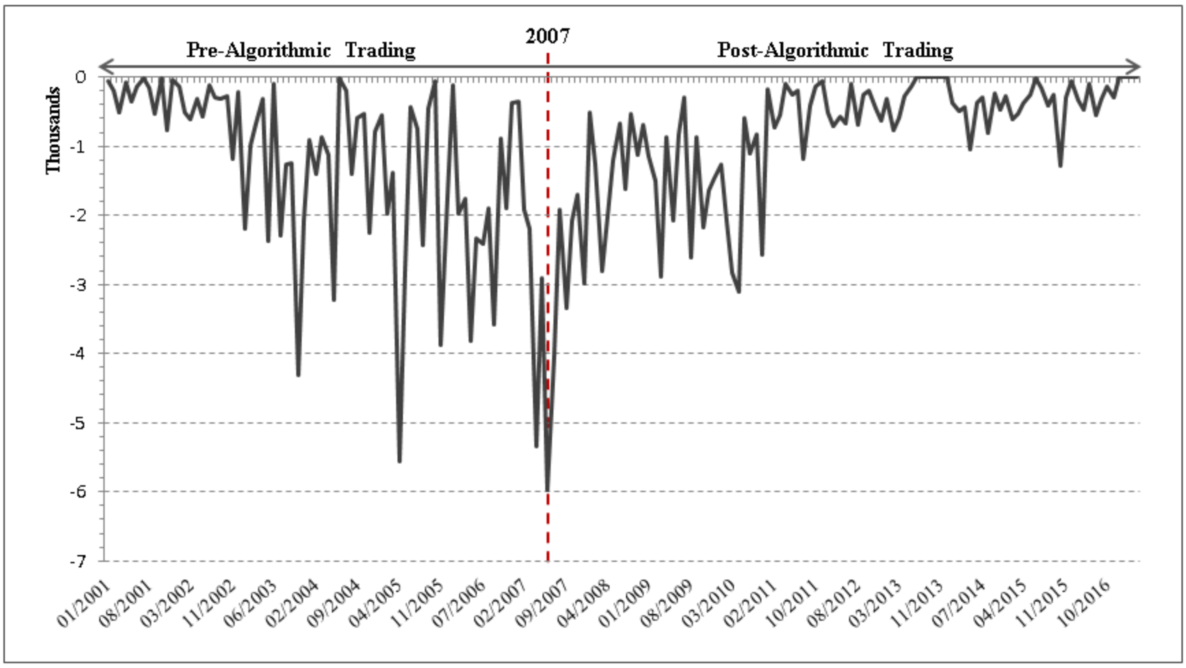


Figure 2. Algorithmic trading measures. This figure depicts the algorithmic trading proxy "Algo Trade", THB volume per message traffic *-1 / 100, on daily basis and highlight the arrival of algorithmic trading in 2007.

4.3 Liquidity Measurement

In some prior studies, it has been found that the bid and ask spreads involve the adverse selection problems for those companies with high information asymmetry. **Ascioglu and al. (2007)** presumes that the bid and ask spreads exacerbate and liquidity decreases in case of information asymmetry. In addition, some prior studies find the positive correlation between trading volume and liquidity. **Lin Sanger and Booth (1995)** presume that the trading volumes imply an adverse selection problem as the informed investors prefer to negotiate important volumes for taking advantage from their private information, thus the rise of trading volumes lead to extra costs that have to recouped by the enlargement of the spreads.

Since the Stock Exchange of Thailand has fixed the bid and ask spreads, we will use other measurements to be proxy of market liquidity. We will obtain trades and market depth at the best bid and best ask level from order submission and deal history. Since we only have order transactions and deal transactions that are submitted the requests to the market including new and cancel requests provided by the SET but not market depth in each minute, we then reconstruct real time market data using their order time and deal time to calculate best bid and best offer price with volume at end of each minute. We use the sequence of order time as main variable and deduct the volume both buy and sell side once deal time of deal transactions have the same time with order time. The auction market is calculated differently. In the auction market, we deduct order volumes based on order number with the open price to be the beginning bid and offer's volume for the next market open session. We will measure market liquidity using (1) liquidity ratio (LR), follows **Baker (1996)**, and (2) market depth (in shares), follows **Frino et al., (2017)**, calculated using total depth at the best bid and best ask level of order submissions at the end of each minute.

The liquidity ratio (LR) measures by using trade volume and price. The higher liquidity ratio denotes the higher liquidity to what extent the high volume of trade has a relative low impact on stock price.

$$LR_{it} = \frac{\sum_{t=1}^{T} P_{it} V_{it}}{\sum_{t=1}^{T} |P_{it} - P_{it-1}|}$$

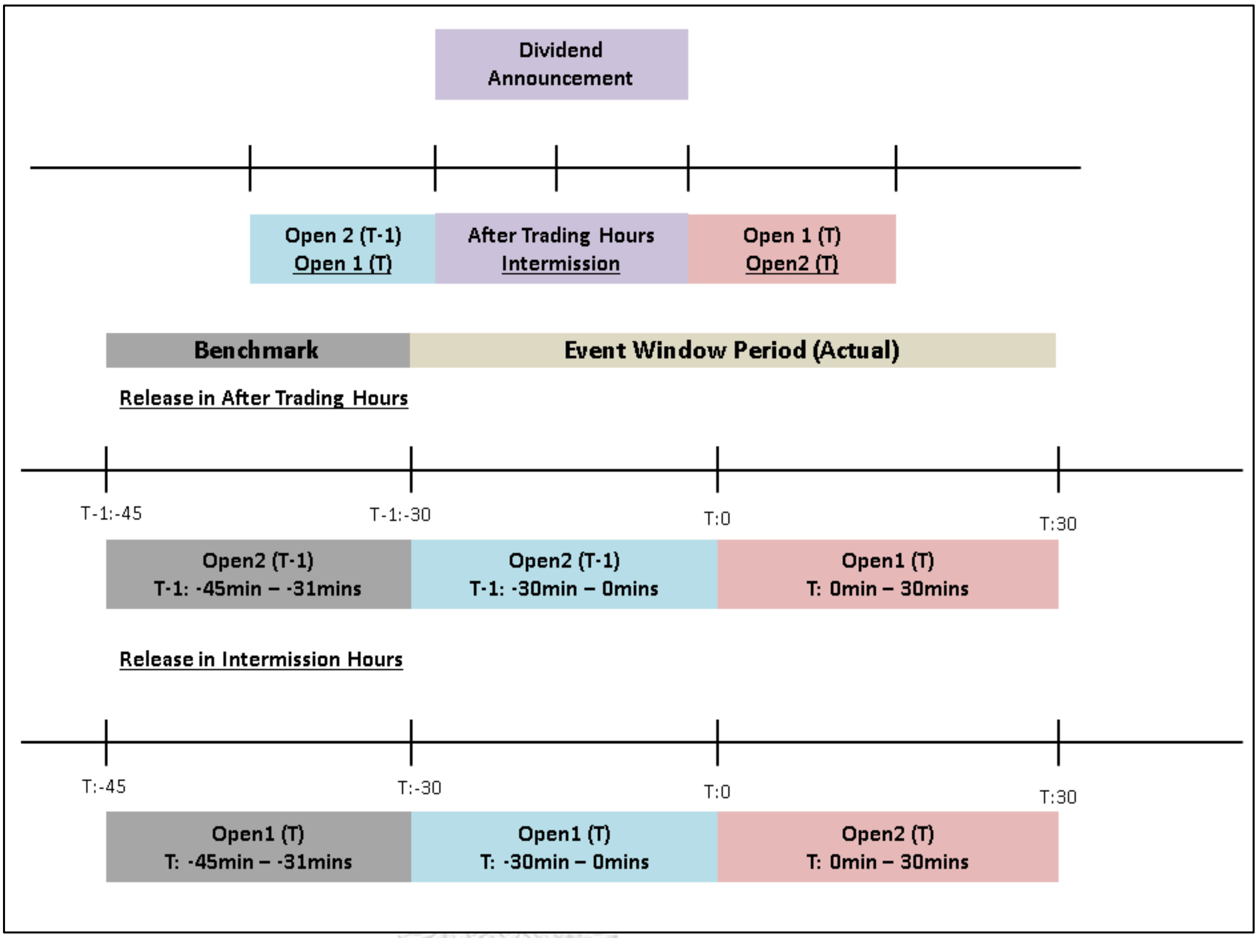
where P_{it} is the price of stock i on time t and V_{it} is the trade volume of stock *i* on time *t*. The denominator measures the absolute price change of the stock over 1-minute interval.

4.4 Event Window Period

We define event window between last -30 minutes in last market trading session before dividend announcement and first +30 minutes in first market open session after each dividend announcement. We then calculate the liquidity measurement with 1-minute interval. The measurement of an excess algorithmic trading impact on market liquidity as:

$$\boldsymbol{Excess_{jd} = Actual_{jd} - \overline{Benchmark}_{jd}}$$

where $Actual_{jd}$ is liquidity ratio and market depth in minute interval *j* for dividend announcement *d*. $\overline{Benchmark}_{jd}$ is the mean liquidity ratio and market depth calculated from last -45 minutes to -31 minutes in last market trading session before dividend announcement *d*.



4.5 Regression Model

Our first hypothesis states that market liquidity is higher in post-algorithmic trading period than pre-algorithmic trading period. In order to test this hypothesis, we will use following regression models to examine changes in market liquidity around dividend announcements between pre-algorithmic trading (before 2007) and post-algorithmic trading (after 2007). We consider applying firm fixed effect. This is because firm is a time-invariant variable that will correlate to itself across different years and thus able to avoid endogeneity problem. We also grouped our sample data into clusters on firms to not overstate the standard errors. This is because our regression model errors independent across clusters, but it is correlated within clusters.

First, we will do univariate analysis on of the difference of each algorithmic trading proxy around dividend announcements between pre-algorithmic trading period and post-algorithmic trading period as following regression model in order to test whether there is a significantly difference between two periods.

$$Liquidity_{jdi} = \beta_0 + \beta_1 \boldsymbol{AlgorithmicTrading_{jdi}} + \boldsymbol{\varepsilon_{jdi}} \qquad (1)$$

where $Liquidity_{jdi}$ is dependent variable for in the regression model for excess liquidity ratio and order and deal transactions[1] for each 1-minute interval j between last -30 minutes in last market trading session before dividend announcement and first +30 minutes in first market open session after each dividend announcement d, event window period, for firm i. $AlgorithmicTrading_{jdi}$ is the proxies of algorithmic trading which are (1) Message Traffics per minute, and (2) Algo_trade.

Then, we will examine whether there is an improvement in market liquidity surrounding dividend announcements in pre-algorithmic trading and post-algorithmic trading environments with following regression model in a multivariate analysis.

$$Liquidity_{jdi} = \beta_0 + \beta_1 PostDiv_{jdi} + \beta_2 PostAlgo_{jdi} + \beta_3 PostDiv_{jdi} PostAlgo_{jdi} + \sum_{k=4}^{7} \beta_k \boldsymbol{X_{kjdi}} + \boldsymbol{\varepsilon_{jdi}} \qquad (2)$$

[1] The excess market depth is calculated by using the actual best bid/offer volume deduct with the benchmark (the average) best bid/offer volume over 15 minutes (benchmark period). The window period explained in 4.4

where $Liquidity_{jdi}$ is dependent variable for in the regression model for excess liquidity ratio and order and deal transactions[1] for each 1-minute interval j between last -30 minutes in last market trading session before dividend announcement and first +30 minutes in first market open session after each dividend announcement d for firm i. $PostDiv_{jdi}$ is a dummy variable equal to 1 if the interval time j is after dividend announcements d for firm i and zero otherwise. $PostAlgo_{jdi}$ is a dummy variable equal to 1 if the interval time j is in the post-algorithmic trading period for firm i and zero otherwise. $PostDiv_{jdi}$ $PostAlgo_{jdi}$ is the interaction term for the interval time j is after dividend announcements d in the post-algorithmic trading period for firm i. X_k is set of control variables compose of log market capitalization, inverse of underlying share price using daily closing price (in THB), volatility and share turnover (annualized).

There are numerous empirical studies finding that market capitalization is a statistically significant determinant of liquidity. **Thomas and Michaely (1988)** further point out that the higher market capitalization should have lower information costs than those with lower market capitalization. This is because larger market capitalization firms are more likely to receive more investment coverage from various financial analysts and also have more public relations department to produce regular updates for investors. **Chan (2000)** also empirically finds that large market capitalization stocks suffer less from information asymmetry.

Bessembinder, Hao and Zheng (2017) find empirical evidence that bid and ask spreads in basis points increase with inverse share price, and that depth in shares increases with inverse share price. Most stock markets in Asia including Thailand use stepwise tick system in which larger tick sizes are imposed on higher priced stocks.

Anshuman and Kalay (1998) presume that the large tick sizes reduce the value of private information. This is because the informed investors will not trade if the trading cost imposed by large tick sizes is greater than the value of private information they possess. Hence, we should observe the negative sign on inverse of underlying share price.

The volatility is measured by using standard deviation open-to-close return based on daily price range that is high minus low (**Parkinson, 1980**). Some prior literatures find that supplying liquidity decreases, in term of spreads widen and depth declines, when volatility is greater. **Domowitz et al. (2001)** point out that there is a strong relationship between liquidity and volatility. Share turnover is a well-known measurement among academics and practitioners to indicate stock liquidity by showing how easy or difficult it is to selling shares of a particular stock on the market (**Hendershott et al., 2011**)

Control Variables	**Measurement**	**Expected Sign**
market capitalization	Log of market capitalization	+
inverse of underlying share price	1 divided by daily closing price	-
volatility	Daily High minus Low price	-
share turnover (annualized)	Deal Trading Volume divided by Listed Shares	+

5. Empirical results

Our analysis begins with a univariate test which shows in **Table 2** reporting a difference in the characteristics of explanation variables between pre-algorithmic trading and post-algorithmic trading periods from their means and t-statistic test. There is statistically significant evidence indicated that sample market conditions are different between pre-algorithmic trading and post-algorithmic trading periods. Market capitalization and inverse of underlying share price show an improvement in term of liquidity in post-algorithmic trading period which are in line with **Thomas and Michaely (1988)** who proposed that large market capitalization stocks suffer less from information asymmetry and **Bessembinder, Hao and Zheng (2017)** who found that bid and ask spreads in basis points increase with inverse share price. In contrast, volatility, on average, is higher and share turnover, on average, is lower which can be interpreted that these characteristics tends to decrease stock market liquidity in post-algorithmic trading period comparing to pre-algorithmic trading period. **Panel A** in **Table 2** reports a sub-sample period during 2007-2009 which is the period of financial crisis, however there is no differences comparing to full sample period.

Table 2

Sample explanatory variables characteristics

This table describes statistics differences of explanation variables between pre-algorithmic trading and post-algorithmic trading periods. The mean differences are measured by t-statistics. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel A: Full Sample					
Explanation variables	Pre-AT Mean	Post-AT Mean	Differences Mean		t-stat
Market capitalization	10.631	11.017	0.386	***	96.547
Inverse of underlying share price	0.113	0.067	-0.046		-37.779
Volatility	1.245	1.665	0.420	***	20.624
Share turnover (annualized)	0.444	0.399	-0.045	***	-7.960
Number Observation	22,692	35,868			

Panel B: Sample Characteristics by sub-sample period					
		Period 2007 - 2009			
Explanation variables	Pre-AT Mean	Post-AT Mean	Differences Mean		t-stat
Market capitalization	10.819	10.718	-0.101	***	-12.710
Inverse of underlying share price	0.093	0.090	-0.003		-1.354
Volatility	1.037	0.993	-0.044		-1.475
Share turnover (annualized)	0.344	0.535	0.191	***	13.793
Number Observation	4,880	8,357			

Market capitalization is the natural log of market capitalization.[2] *Inverse of underlying share price* uses one divided by daily closing price. *Volatility* is the daily high minus low price[3] . *Share turnover* (annualized) calculated by using deal trading volume divided by listed shares. All variables collect on after dividend announcement dates (the period explained in 4.4) and all variables are all in daily basis.

[2] Taking the log would make the distribution of market capitalization appear more normal.

[3] The volatility measure by using standard deviation open-to-close return based on daily price range that is high minus low (Parkinson, 1980).

5.1 Algorithmic Trading activity around dividend announcement days

We first examine the change in the algorithmic trading proxies around dividend announcement days in pre-algorithmic trading period and post-algorithmic trading period. **Table 3** reports the summary statistics for our algorithmic trading proxies including message traffic per minute and Algo Trade around dividend announcement days in pre-algorithmic trading and post-algorithmic trading periods in daily basis over 960 observations. This table reports that there is statistically significant evidence showing that message traffic per minute, significant at the 1% level of significance, and Algo Trade, significant at the 1% level of significance, have been increased in post-algorithmic trading period. This indicates that these proxies in post-algorithmic trading period are very difference from pre-algorithmic trading period, in other word; our proxies illustrate that there is an increase in the intensity of order submissions and cancellations from the market participants who employ algorithms in trading during post-algorithmic trading which in line with **Figure 1** and **Figure 2**.

Table 3

Algorithmic trading proxies (Message Traffic counts per 1 minute interval and Algo Trade)
This table reports the summary statistics for algorithmic trading proxies in pre-algorithmic trading and post-algorithmic trading periods. This table uses a t-test to compare the daily mean of all algorithmic trading activity proxies. *,**,*** denotes significance at the 10%, 5* and 1% level, respectively

	Message Traffic	**Algo Trade**
Pre-Algorithmic trading period	4.2503	-117.7746
Post-Algorithmic trading period	7.3119	-40.2790
Difference	3.0616***	77.5055***
t-stat	19.3707	2.8312
Number of Observations	960	960

Table 4 shows the results of linear regression model, supporting *hypothesis 1*, the coefficient of Algorithmic Trading in **Panel A** which is the proxy of (1) Message Traffics has a positive sign with 1% significant level for excess liquidity ratio. It can be implied that the liquidity ratio improves with the message traffics, in other word; the liquidity ratio has a positive relation to the liquidity. On the other hand, the Message Traffics has a negative sign with 1% significant level for excess market depth both best offer and best bid. **Panel B** shows the proxy of (2) Algo Trade, it has a negative sign for excess liquidity and a positive sign for excess market depths. These results indicate that the lesser negative value of the Algo Trade proxy, the greater for excess liquidity ratio and excess market depths. Noted that Algo Trade proxy is in negative term which can be implied that the higher message traffics, the lesser negative value of this proxy. These findings imply that the algorithmic trading has a positive relation to stock market liquidity ratio surrounding dividend announcements while it has a negative relation to stock market depth both bid and offer at first level surrounding dividend announcements.

Table 4

Algorithmic trading proxies from pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimate of regression analysis for the entry of algorithmic trading has a positive relation to stock market liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations included firm fixed effect. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel A: Message Traffic (per minute)			
Firm fixed effect	Yes	Yes	Yes
Parameters	(1) Excess_Liquidity	(2) Excess_Offer	(3) Excess_Bid
Message Traffics	237.10***	-21,293.65***	-53,931.89***
	(0.000)	(0.000)	(0.000)
Constant	5,359.12***	-1133160.25***	-1344823.38***
	(0.000)	(0.000)	(0.000)
Observations	58,560	58,560	58,560
R-squared	0.020	0.011	0.018
Number of Firms	63	63	63
Panel B: Algo Trade			
Firm fixed effect	Yes	Yes	Yes
Parameters	(1) Excess_Liquidity	(2) Excess_Offer	(3) Excess_Bid
Algo Trade	-52.24***	-650.82***	170.32
	(0.000)	(0.000)	(0.514)
Constant	7,096.60***	-1297639.63***	-1758538.63***
	(0.000)	(0.000)	(0.000)
Observations	58,560	58,560	58,560
R-squared	0.041	0.0004	0.0000
Number of Firms	63	63	63

5.2 Liquidity around dividend announcement days

Turning our analysis to our intraday analysis around dividend announcements, **Table 5** reports significant tests on the difference in liquidity measurements includes liquidity ratio and market depths (best bid and best offer) in pre-algorithmic and post-algorithmic periods for 1 minute intervals surrounding dividend announcements releases from -30 to +30 minutes. The result in **Panel A Table 5** shows a positive change in excess liquidity ratio from the second to the fifth minute after the dividend announcement releases. **Panel B Table 5** and **Panel C Table 5** report the difference in excess market depth for both best offer and best bid level between two periods significantly decrease in the first minute after the dividend announcement releases.

Figure 3 plots the excess liquidity ratio in pre-algorithmic trading and post-algorithmic trading periods. Before dividend announcements, excess liquidity ratio between pre-algorithmic trading and post-algorithmic trading periods is indistinguishable. After the dividend announcement releases, excess liquidity ratio in both periods increase rapidly and then fall sharply into the same level as before the announcement releases. However, the excess liquidity ratio in post-algorithmic trading period increases higher almost double than in pre-algorithmic trading period. **Panel A Table 5** and **Figure 3** provide evidence that can be interpreted that the liquidity ratio improves significantly after the dividend announcement releases in post-algorithmic trading period.

Table 5

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) in pre-algorithmic and post-algorithmic periods. This table reports the result of a paired t-test for every 1 minute interval. This table shows the difference of mean Liquidity ratio, in panel A, and Market Depth, in panel B and Panel C, between pre-algorithmic trading and post-algorithmic trading periods. *,**,*** denotes significance at the 10%, 5* and 1% level, respectively

	Panel A			Panel B			Panel C		
1 Min	Excess Liquidity			Excess Offer			Excess Bid		
Interval	PostAT-PreAT		t-stat	PostAT-PreAT		t-stat	PostAT-PreAT		t-stat
-30	4,421.69		(1.25)	128,172.23	**	(2.17)	253,410.73	***	(3.66)
-29	7,845.19		(1.31)	198,695.65	***	(2.88)	289,662.08	***	(3.17)
-28	200.92		(0.05)	209,404.64	**	(2.49)	388,853.69	***	(3.52)
-27	3,748.77		(0.93)	204,615.84	**	(2.10)	459,021.90	***	(3.39)
-26	3,115.56		(0.92)	220,087.86	**	(2.20)	482,356.09	***	(3.40)
-25	(2,727.33)		0.42	222,565.09	***	(2.61)	546,658.26	***	(4.07)
-24	(2,774.75)		1.02	238,715.27	***	(2.69)	556,759.15	***	(4.12)
-23	(180.15)		0.07	292,997.02	***	(3.31)	606,061.99	***	(4.29)
-22	4,952.23		(0.76)	311,744.46	***	(3.51)	644,829.33	***	(4.16)
-21	(4,127.78)	**	2.25	299,029.23	***	(2.97)	709,436.18	***	(4.44)
-20	2,088.24		(0.83)	305,089.98	***	(2.91)	746,110.38	***	(4.51)
-19	756.30		(0.24)	322,024.56	***	(2.99)	744,907.74	***	(4.62)
-18	(2,814.53)		0.73	368,218.10	***	(3.15)	725,572.11	***	(4.35)
-17	2,645.96		(0.72)	379,744.63	***	(3.13)	700,023.84	***	(3.91)
-16	881.91		(0.19)	408,601.03	***	(3.34)	743,504.07	***	(3.93)
-15	(3,199.78)		0.83	520,156.17	***	(4.36)	901,244.73	***	(4.49)
-14	2,460.77		(0.92)	380,260.23	***	(2.72)	750,322.66	***	(3.58)
-13	(2,335.54)		0.68	431,686.86	***	(3.14)	721,313.11	***	(3.35)
-12	182.80		(0.07)	409,865.02	***	(2.78)	733,782.62	***	(3.18)
-11	(1,566.21)		0.44	453,950.40	***	(3.07)	748,229.10	***	(3.02)
-10	7,008.36		(0.89)	474,504.30	***	(3.23)	799,062.17	***	(3.12)
-9	3,406.71		(0.92)	500,323.48	***	(3.37)	828,445.02	***	(3.20)
-8	3,522.23		(1.12)	512,081.30	***	(3.29)	827,868.97	***	(3.17)
-7	4,633.93		(0.85)	534,985.74	***	(3.27)	861,421.37	***	(3.21)
-6	2,869.83		(0.65)	533,705.57	***	(3.23)	906,094.69	***	(3.35)
-5	6,206.66	*	(1.75)	521,347.55	***	(3.15)	925,874.34	***	(3.35)
-4	1,009.79		(0.28)	595,217.61	***	(3.60)	1,007,770.76	***	(3.57)
-3	10,279.01	**	(2.35)	602,835.79	***	(3.63)	976,104.18	***	(3.50)
-2	(4,137.79)	**	2.47	609,894.22	***	(3.68)	988,015.90	***	(3.54)
-1	(1,347.47)		0.54	607,717.42	***	(3.64)	1,000,352.08	***	(3.57)
0	5,074.06		(0.33)	(3,535,265.70)	***	3.44	(3,651,346.29)	**	2.01
1	8,727.90		(1.50)	(3,606,291.14)	***	3.66	(3,617,786.93)	**	2.00
2	14,790.86	**	(2.25)	(3,611,359.28)	***	3.70	(3,627,498.44)	**	2.01

Table 5 (continues)

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) from pre-algorithmic and post-algorithmic periods. This table reports the result of a paired t-test for every 1 minute interval. This table shows the difference of mean Liquidity ratio, in panel A, and Market Depth, in panel B and Panel C, between pre-algorithmic and post-algorithmic periods. *,**,*** denotes significance at the 10%, 5* and 1% level, respectively

	Panel A			Panel B			Panel C		
1 Min	Excess Liquidity			Excess Offer			Excess Bid		
Interval	PostAT-PreAT		t-stat	PostAT-PreAT		t-stat	PostAT-PreAT		t-stat
3	5,926.83		(0.71)	(3,496,143.19)	***	3.61	(3,481,803.80)	*	1.93
4	14,894.46	**	(1.99)	(3,541,469.16)	***	3.66	(3,458,802.25)	*	1.92
5	12,909.09	***	(2.92)	(3,554,947.13)	***	3.66	(3,475,187.73)	*	1.93
6	623.20		(0.12)	(3,398,773.56)	***	3.57	(3,326,142.99)	*	1.86
7	(1,531.48)		0.32	(3,296,821.09)	***	3.50	(3,292,312.78)	*	1.85
8	7,496.20	*	(1.86)	(3,245,958.54)	***	3.47	(3,213,974.17)	*	1.82
9	2,198.69		(0.58)	(3,186,045.20)	***	3.45	(3,129,940.03)	*	1.78
10	6,289.62		(1.56)	(3,120,585.53)	***	3.40	(3,065,280.62)	*	1.74
11	7,962.24	*	(1.76)	(3,167,335.79)	***	3.46	(3,087,224.72)	*	1.76
12	9,892.64	**	(2.20)	(3,114,459.53)	***	3.42	(3,116,282.16)	*	1.78
13	7,056.69		(1.27)	(3,121,026.37)	***	3.54	(3,101,851.49)	*	1.77
14	4,267.34		(1.05)	(3,148,126.59)	***	3.54	(3,124,694.41)	*	1.79
15	121.55		(0.03)	(3,171,626.01)	***	3.66	(3,161,155.87)	*	1.81
16	8,363.11	*	(1.82)	(3,144,439.98)	***	3.63	(3,069,781.37)	*	1.76
17	2,955.45		(0.50)	(3,135,943.00)	***	3.62	(3,052,876.09)	*	1.75
18	3,458.88		(0.96)	(3,142,463.73)	***	3.67	(2,957,873.37)	*	1.70
19	8,206.99	*	(1.82)	(3,155,127.62)	***	3.76	(2,919,926.24)	*	1.68
20	6,438.32		(1.58)	(3,075,260.43)	***	3.68	(2,877,205.97)	*	1.66
21	5,421.87		(1.50)	(3,127,109.92)	***	3.82	(2,847,241.60)		1.64
22	599.55		(0.15)	(3,093,063.61)	***	3.79	(2,830,105.95)		1.63
23	1,298.31		(0.30)	(3,124,027.04)	***	3.90	(2,859,145.79)	*	1.65
24	2,744.93		(0.68)	(3,139,640.32)	***	3.92	(2,869,509.75)	*	1.66
25	11,923.44	*	(1.85)	(3,107,414.49)	***	3.89	(2,866,374.66)	*	1.66
26	8,143.13		(1.48)	(3,042,156.58)	***	3.84	(2,828,678.22)		1.64
27	8,386.26	**	(1.97)	(3,036,561.08)	***	3.84	(2,802,893.42)		1.63
28	3,965.00		(0.74)	(3,002,144.20)	***	3.80	(2,783,481.61)		1.61
29	12,315.58	*	(1.88)	(3,062,768.40)	***	3.94	(2,781,111.79)		1.62
30	9,645.87	**	(2.12)	(3,043,414.22)	***	3.92	(2,729,036.43)		1.59

In contrast, **Panel B Table 5** and **Panel C Table 5** together with **Figure 4** and **Figure 5** provide evidence consistent with **Lee, Mucklow, and Ready (1993)** who proposed that market makers widen spreads and reduce market depth in anticipation of upcoming public news announcements. The excess market depth for best offer and best bid level sharply decline after dividend announcements in both periods. Then those market depths slightly recover to the same market depths level more than 30 minutes after dividend announcement releases. A significant different trend depicted in these figures illustrate even though the algorithmic trading system has an advantage of fast technology to adjust their position and manage their risk exposure, this result indicates that their participation do not help to provide liquidity in term of market depths in the stock market.

Table 6 reports the results of linear regression model to assess the changes in liquidity around dividend announcements in pre-algorithmic and post-algorithmic periods based on following model:

$$Liquidity_{jdi} = \beta_0 + \beta_1 PostDiv_{jdi} + \beta_2 PostAlgo_{jdi} + \beta_3 PostDiv_{jdi} PostAlgo_{jdi} + \sum_{k=4}^{7} \beta_k \boldsymbol{X_{kjdi}} + \boldsymbol{\varepsilon_{jdi}}$$

Supporting *hypothesis 2*, the coefficient on the interaction term β_3, our primary variable of interest, which captures the variation in liquidity measurements, liquidity ratio and market depths, after dividend announcement releases in post-algorithmic trading period. The result shows that it has a positive sign with statistically significant at the 10% level for excess liquidity. Our evidence indicates that the liquidity ratio significantly improves after the announcement consistent with those reports in **Panel A Table 5** and **Figure 3**. In contrast, β_3 has a negative sign with statistically significant at the 1% level for market depth at best offer and at 5% level for best bid. The results of market depths are also consistent with those reports in **Panel B and C in Table 5** with **Figure 4 and 5**. These results remain significant regardless of the included control variables[4].

[4] The corresponding linear regression model are reported in Appendix A

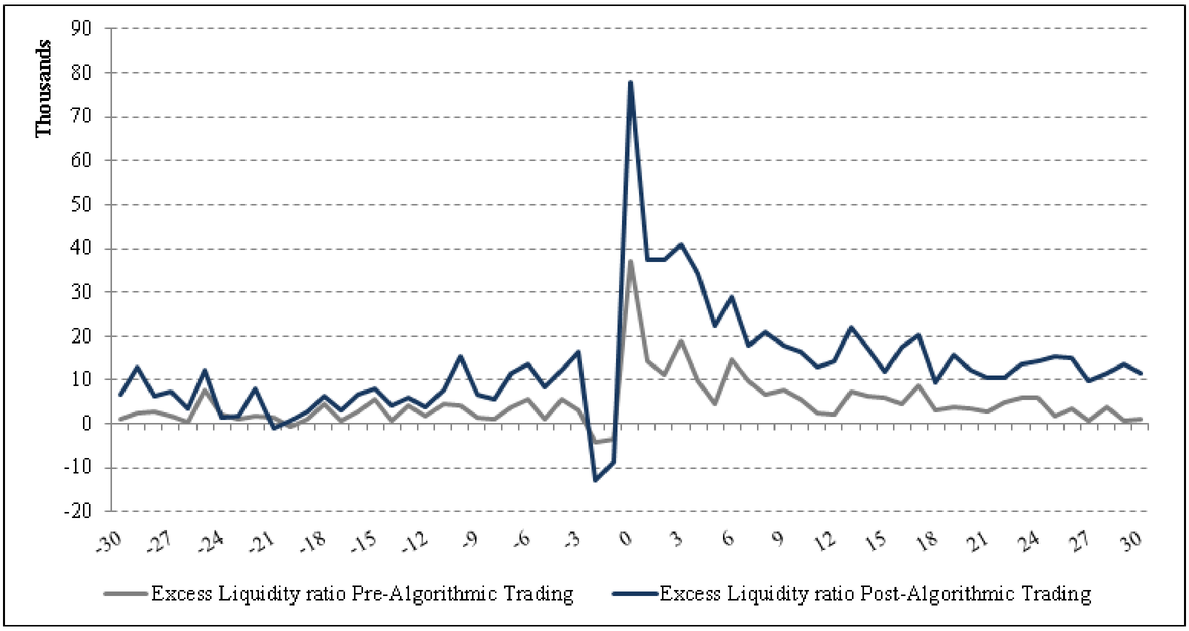


Figure 3. Excess liquidity ratio, trading volume * price divided by change in price over 1-minute interval, around dividend announcements in Pre-Algorithmic trading and Post-Algorithmic trading period. This figure depicts mean excess liquidity ratio for each 1-minute interval from -30 to +30 minutes around dividend announcements. Excess liquidity ratio is calculated as the difference between the actual value for each 1-minute interval and a benchmark value calculated as the mean from -45 to -31 minutes before the announcement time.

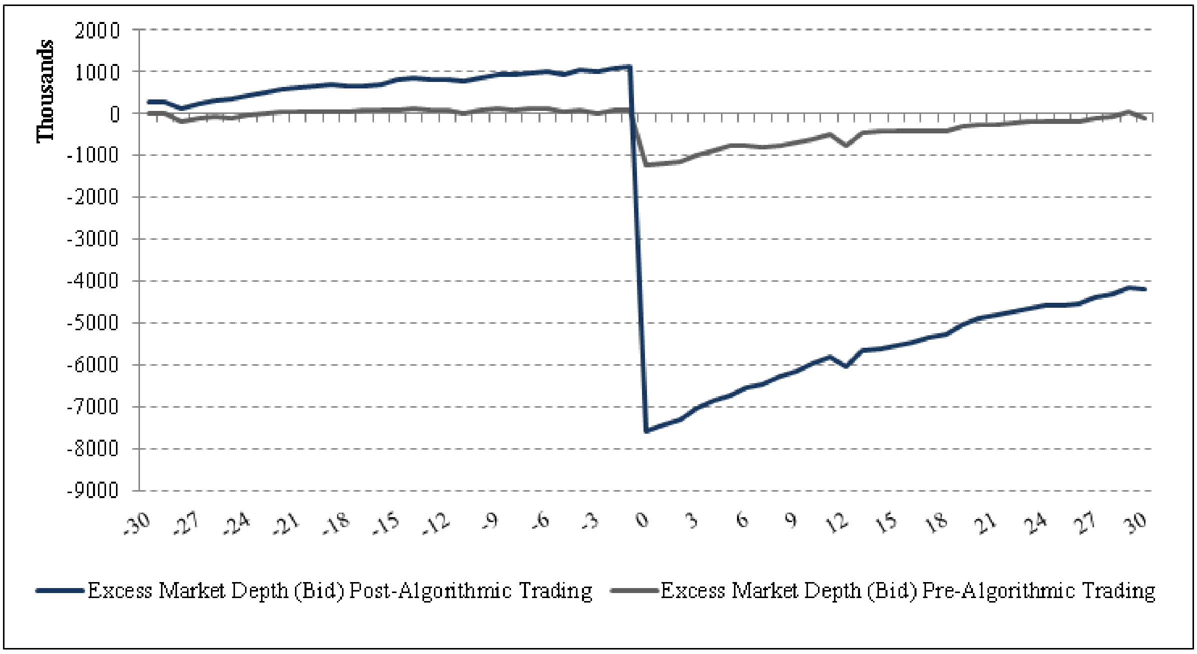


Figure 4. Excess market depth (Bid) around dividend announcements in Pre-Algorithmic trading and Post-Algorithmic trading period. This figure depicts mean excess market depth (Bid) for each 1-minute interval from -30 to +30 minutes around dividend announcements. Excess market depth (Bid) is calculated as the difference between the actual value for each 1-minute interval and a benchmark value calculated as the mean from -45 to -31 minutes before the announcement time.

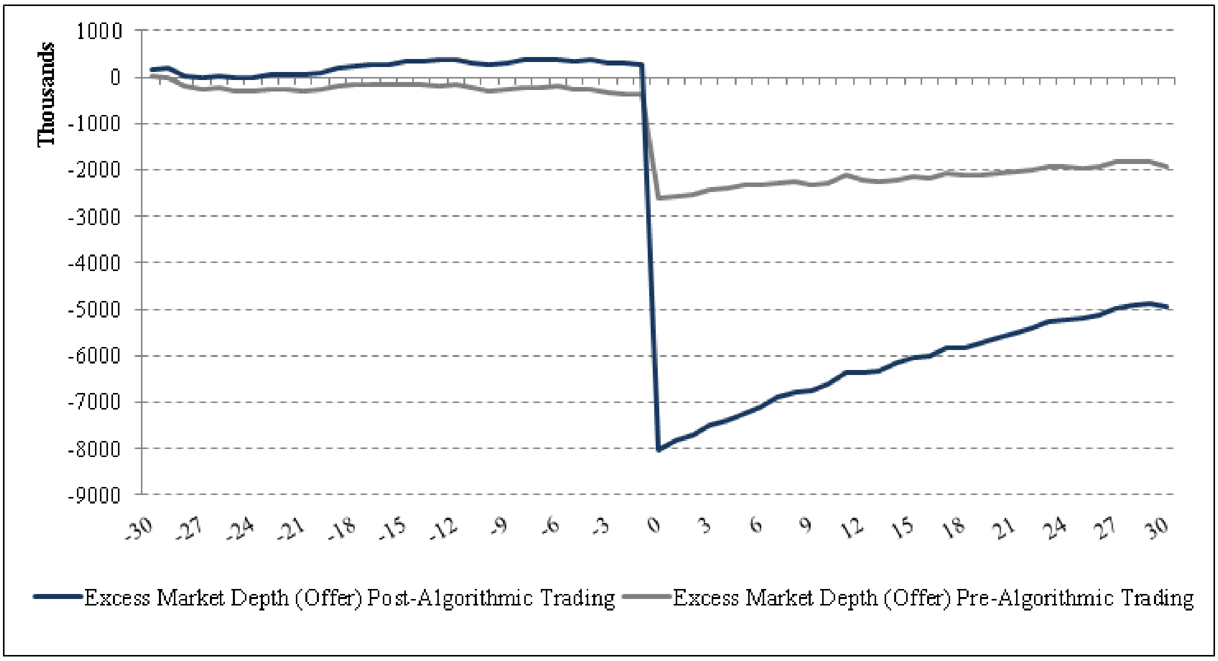


Figure 5. Excess market depth (Offer) around dividend announcements in Pre-Algorithmic trading and Post-Algorithmic trading period. This figure depicts mean excess market depth (Offer) for each 1-minute interval from -30 to +30 minutes around dividend announcements. Excess market depth (Offer) is calculated as the difference between the actual value for each 1-minute interval and a benchmark value calculated as the mean from -45 to -31 minutes before the announcement time.

Table 6

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) between pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimates of regression analysis for changes in liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations is as follows:

$$Liquidity_{jdi} = \beta_0 + \beta_1 PostDiv_{jdi} + \beta_2 PostAlgo_{jdi} + \beta_3 PostDiv_{jdi} PostAlgo_{jdi} + \sum_{k=4}^{7} \beta_k \boldsymbol{X_{kjdi}} + \boldsymbol{\varepsilon_{jdi}}$$

where $Liquidity_{jdi}$ is dependent variable for in the regression model for excess liquidity ratio and excess market depth from best bid and best ask from order submissions for each 1-minute interval j between last -30 mins in last market trading session before dividend announcement and first +30 mins in first market open session after each dividend announcement d for firm i. $PostDiv_{jdi}$ is a dummy variable equal to 1 if the interval time j is after dividend announcements d for firm i and zero otherwise. $PostAlgo_{jdi}$ is a dummy variable equal to 1 if the interval time j is in the post-algorithmic trading period for firm i and zero otherwise. X_k is set of control variables compose of log market capitalization, inverse of underlying share price using daily closing price (in THB), volatility and share turnover (annualized). In parentheses is p-value for statistical significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively. The robust standard errors are clustered by firm. Firm fixed effect is also applied.

Firm fixed effect	Yes	Yes	Yes
Parameters	(1) Excess_Liquidity	(2) Excess_Offer	(3) Excess_Bid
PostDiv	4,890***	-912,211***	-1,893,791***
	(0.000)	(0.000)	(0.000)
PostAlgo	-3,031***	86,270	-523,265**
	(0.004)	(0.503)	(0.041)
PostDiv_PostAlgo	4,902***	-3,610,945***	-3,816,087***
	(0.000)	(0.000)	(0.000)
Ln_MarCap	11,943***	3,905,420***	9,903,881***
	(0.000)	(0.000)	(0.000)
Inverse_SP	9,244*	17,549,410***	39,718,212***
	(0.067)	(0.000)	(0.000)
volatility	1,564***	-41,695*	-205,978***
	(0.000)	(0.064)	(0.000)
sh_turnover	9,886***	-6,756	-995,719***
	(0.000)	(0.933)	(0.000)
Constant	-132,020***	-43,629,592***	-109,568,632***
	(0.000)	(0.000)	(0.000)
Observations	58,560	58,560	58,560
R-squared	0.011	0.054	0.035
Number of Firms	63	63	63

In addition, the coefficient of β_1 for PostDiv dummy variable is also significant at 1% for excess liquidity. This coefficient contains both pre-algorithmic trading and post-algorithmic trading period, thus it seems that the number of trading volumes over the price changes have been increased. A possible explanation could be that the price after dividend announcements generally decrease with the amount of dividend paid, thus it may decrease the amount of trading volume from the group of traders who prefer not to receive dividend before the announcements. And the number of trading volumes increase after the announcements given the price movement remain constant. In contrast to the market depths that all traders seem to fear to provide those trading orders at first level after the announcements consistent with **Lee, Mucklow, and Ready (1993)**.

Moreover, the coefficient of β_2 for PostAlgo dummy variable is also significant at 5% with a negative sign. This can be interpreted that the excess liquidity ratio in post-algorithmic trading period tends to consume liquidity rather than providing liquidity to the stock market. On the other hand, it has a positive sign for those excess market depths. This coefficient contains both before dividend announcement and after dividend announcement window period. A possible explanation could be that the price movement may be more extreme in post-algorithmic trading period in Thai stock market in nearly end of the trading session with the anticipation of upcoming public new announcements since it has more powerful participants in the market like an algorithmic trading given the trading volumes remain constant. However, once we interpret it together with our primary interest variable, the interaction term β_3, it has a positive value meaning that the algorithmic trading does improve liquidity ratio.

These findings imply that algorithmic trading support liquidity in term of trading volume in the stock market during times of information asymmetry. However, algorithmic trading does not support to provide market depths at first level for trading. Recall, **Hendershott and Riordan (2011)** who proposed that algorithmic trading could predict price changes over short horizons of less than 30 seconds and their marketable order's informational advantage is sufficient to overcome the bid and ask spreads and trading fees to generate positive trading revenues. **Foucault et al. (2003)** who suggested that liquidity suppliers should spend monitoring cost to reduce the free trading option's cost. This cost involves the adverse selection cost of being picked off on liquidity suppliers. And **Rock (1990)** presumed that if some traders are better at avoiding being picked off, they can impose adverse selection costs on other liquidity suppliers, and thus drive out other liquidity suppliers from the stock market

Therefore, one possible explanations about these relationships between Algorithmic Trading and the stock market liquidity is that the market participant employing algorithmic trading systems with fast and high technology are better in timing their trade and also have the ability to predict the price changes over the short time may want to limit their risk exposure by not act as liquidity suppliers who provide standing orders in the stock market as a free trading option to other traders to avoid being pick off but may rather to submit their orders when the price and volume meet their own strategies' criteria based on their own prediction. As opposed to uninformed non-algorithmic traders who may be afraid to trade against informed traders in the situation of having high probability of information asymmetry such a dividend announcement resulted in an improvement of liquidity ratio with a sharp deduction in market depths.

6. Conclusion

Our paper attempts to provide an investigation of stock market liquidity patterns surrounding dividend announcements in pre-algorithmic and post-algorithmic trading periods on the Stock Exchange of Thailand during 2001 to 2016. The Stock Exchange of Thailand has initiated the algorithmic trading in 2007. Our study has two key empirical findings. First, the algorithmic trading has a positive relation to stock market liquidity ratio but has a negative relation to market depths for both bid and offer at first level. Second, we find empirical evidence that trading volume is higher in post-algorithmic trading period than in pre-algorithmic trading period while market depths for bid and offer, surprisingly, are lower in post-algorithmic trading period than in pre-algorithmic trading period. Our evidence shows that algorithmic trading does support trading volume following the dividend announcement.

A possible explanation is that the market participant who employ algorithmic trading systems may want to limit the amount of risk they face from the increase of adverse selection cost similar to uninformed non-algorithmic traders resulted in a significantly drop in market depths. However, since they employ the fast and high trading technology, they are able to predict the change in price in short time horizon and also better in timing their trade. Thus, they may decide to submit their orders when the price and volume meet their own strategies' criteria based on their own prediction without provide standing orders in the market which may incur adverse selection cost of being picked off as being a liquidity supplier.

In conclusion, our paper provides empirical evidence to support the hypothesis that the entry of algorithmic trading in Thai stock market and their increase activity in the market able to make such an improvement in stock market liquidity especially after the dividend announcement releases. A more detailed analysis would be useful to learn the extent to which drivers affect the stock market depths drop to following the dividend announcement after the entry of algorithmic trading.

Appendix A

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) in pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimates of regression analysis for changes in liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations. The robust standard errors are clustered by firm. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel A: Excess Liquidity Ratio

Parameters	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostDiv	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88
	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)
PostAlgo	719,102.31***	600,632.13	194,195.00	680,960.94***	573,774.19***	626,608.25	633,280.13	712,078.88
	(0.001)	(0.164)	(0.565)	(0.001)	(0.004)	(0.139)	(0.150)	(0.102)
PostDiv_PostAlgo	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Ln_MarCap		306,842.31				-1352618.13*	125,062.51	-387,755.75
		(0.762)				(0.074)	(0.899)	(0.687)
Inverse_SP			-11385711.00			-13334103.00*		
			(0.105)			(0.059)		
sh_turnover				-855,039.25			-841,473.50	
				(0.272)			(0.271)	
volatility					345,878.09**			373,023.59**
					(0.034)			(0.011)
Constant	-49,004.29	-3311038.75	1,239,919.50	330,614.75	-479,492.34**	15840143.00*	-1004945.19	3,608,945.25
	(0.644)	(0.759)	(0.116)	(0.242)	(0.046)	(0.054)	(0.924)	(0.724)
Observations	58,560	58,560	58,560	58,560	58,560	58,560	58,560	58,560
R-squared	0.016	0.016	0.022	0.016	0.017	0.023	0.016	0.017

Appendix A (continued)

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) in pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimates of regression analysis for changes in liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations. The robust standard errors are clustered by firm. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel A: Excess Liquidity Ratio (Continued)

Parameters	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
PostDiv	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88
	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)
PostAlgo	164,089.81	162,955.19	540,495.75***	663,677.63	702,116.75	747,827.19*	134,436.02	741,321.88
	(0.633)	(0.625)	(0.008)	(0.131)	(0.115)	(0.093)	(0.692)	(0.109)
PostAlgo_PostDiv	-3816087.00**	- 3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Ln_MarCap				-1581644.63**	-1736586.63**	-588,031.44		-1977168.50**
				(0.040)	(0.037)	(0.536)		(0.021)
Inverse_SP	-11276845.00	-10509804.00		-13533291.00*	-12562647.00*		-10431762.00	-12749928.00*
	(0.108)	(0.133)		(0.058)	(0.071)		(0.136)	(0.070)
sh_turnover	-787,400.06		-814,614.63	-945,430.00		-873,547.69	-772,787.50	-961,646.31
	(0.311)		(0.293)	(0.225)		(0.252)	(0.320)	(0.217)
volatility		170,456.89**	338,596.19**		257,765.16**	379,235.50**	164,851.47**	262,885.28**
		(0.045)	(0.036)		(0.021)	(0.013)	(0.048)	(0.025)
Constant	1,577,184.00*	928,607.44	-108,757.73	18717220.00**	19513952.00**	6,118,177.00	1,269,850.38	22513352.00**
	(0.093)	(0.245)	(0.672)	(0.028)	(0.029)	(0.544)	(0.174)	(0.016)
Observations	58,560	58,560	58,560	58,560	58,560	58,560	58,560	58,560
R-squared	0.023	0.022	0.018	0.024	0.024	0.018	0.023	0.025

Appendix A (continued)

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) in pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimates of regression analysis for changes in liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations. The robust standard errors are clustered by firm. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel B: Excess Offer (Market Depth)

Parameters	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostDiv	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13
	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)
PostAlgo	393,274.56***	299,214.84*	70,511.32	378,280.66***	288,728.72**	314,999.59*	311,519.19*	378,836.84**
	(0.003)	(0.071)	(0.647)	(0.004)	(0.029)	(0.074)	(0.067)	(0.027)
PostAlgo_PostDiv	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln_MarCap		243,618.31				-764,776.00*	175,109.33	-252,630.27
		(0.550)				(0.066)	(0.662)	(0.494)
Inverse_SP			-7001024.50**			-8102654.00**		
			(0.046)			(0.031)		
sh_turnover				-336,128.16			-317,133.69	
				(0.498)			(0.524)	
volatility					248,817.14***			266,502.94***
					(0.010)			(0.005)
Constant	50,070.94	-2539830.50	842,624.63**	199,304.61	-259,612.77*	9,097,653.00*	-1670712.13	2,404,082.50
	(0.403)	(0.559)	(0.035)	(0.323)	(0.051)	(0.052)	(0.696)	(0.542)
Observations	58,560	58,560	58,560	58,560	58,560	58,560	58,560	58,560
R-squared	0.039	0.039	0.048	0.039	0.042	0.049	0.039	0.043

Appendix A (continued)

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) in pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimates of regression analysis for changes in liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations. The robust standard errors are clustered by firm. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel B: Excess Offer (Market Depth) (Continued)

Parameters	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
PostDiv	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13	-912,211.13
	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)
PostAlgo	59,256.11	44,057.66	276,197.44**	329,898.59*	372,880.44**	392,745.69**	33,659.28	388,874.28*
	(0.700)	(0.777)	(0.038)	(0.076)	(0.050)	(0.026)	(0.829)	(0.052)
PostAlgo_PostDiv	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***	-3610944.50***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln_MarCap				-856,826.88**	-1059106.00**	-330,553.06		-1157252.13**
				(0.039)	(0.018)	(0.370)		(0.011)
Inverse_SP	-6960324.00**	-6259313.00*		-8182712.50**	-7511296.50**		-6230858.00*	-7587698.50**
	(0.047)	(0.070)		(0.030)	(0.039)		(0.072)	(0.038)
sh_turnover	-294,379.72		-306,749.50	-379,989.53		-339,877.84	-281,766.31	-392,306.84
	(0.568)		(0.536)	(0.468)		(0.496)	(0.583)	(0.454)
volatility		144,341.70**	246,075.08**		197,589.09***	268,919.88***	142,297.92**	199,677.88***
		(0.014)	(0.010)		(0.007)	(0.006)	(0.014)	(0.008)
Constant	968,715.31**	579,007.75	-120,009.74	10254014.00**	11913800.00**	3,380,368.25	703,428.44	13137415.00***
	(0.039)	(0.150)	(0.551)	(0.030)	(0.016)	(0.393)	(0.126)	(0.010)
Observations	58,560	58,560	58,560	58,560	58,560	58,560	58,560	58,560
R-squared	0.049	0.049	0.043	0.050	0.051	0.043	0.050	0.052

Appendix A (continued)

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) in pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimates of regression analysis for changes in liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations. The robust standard errors are clustered by firm. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel C: Excess_Bid (Market Depth)

Parameters	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostDiv	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88
	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)
PostAlgo	719,102.31***	600,632.13	194,195.00	680,960.94***	573,774.19***	626,608.25	633,280.13	712,078.88
	(0.001)	(0.164)	(0.565)	(0.001)	(0.004)	(0.139)	(0.150)	(0.102)
PostAlgo_PostDiv	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Ln_MarCap		306,842.31				-1352618.13*	125,062.51	-387,755.75
		(0.762)				(0.074)	(0.899)	(0.687)
Inverse_SP			-11385711.00			-13334103.00*		
			(0.105)			(0.059)		
sh_turnover				-855,039.25			-841,473.50	
				(0.272)			(0.271)	
volatility					345,878.09**			373,023.59**
					(0.034)			(0.011)
Constant	-49,004.29	-3311038.75	1,239,919.50	330,614.75	-479,492.34**	15840143.00*	-1004945.19	3,608,945.25
	(0.644)	(0.759)	(0.116)	(0.242)	(0.046)	(0.054)	(0.924)	(0.724)
Observations	58,560	58,560	58,560	58,560	58,560	58,560	58,560	58,560
R-squared	0.016	0.016	0.022	0.016	0.017	0.023	0.016	0.017

Appendix A (continued)

Changes in liquidity (Liquidity ratio and Market depths at best bid and best offer level) in pre-algorithmic and post-algorithmic periods surrounding dividend announcements. This table reports coefficients estimates of regression analysis for changes in liquidity around dividend announcements using data during 2001 to 2016. The regression model that we used to estimate over 58,560 observations. The robust standard errors are clustered by firm. In parentheses is p-value for statistically significant. *, **, *** denotes significance at the 10%, 5* and 1% level, respectively.

Panel C: Excess_Bid (Market Depth) (continued)

Parameters	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
PostDiv	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88	-1893790.88
	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)
PostAlgo	164,089.81	162,955.19	540,495.75***	663,677.63	702,116.75	747,827.19*	134,436.02	741,321.88
	(0.633)	(0.625)	(0.008)	(0.131)	(0.115)	(0.093)	(0.692)	(0.109)
PostAlgo_PostDiv	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**	-3816087.00**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Ln_MarCap				-1581644.63**	-1736586.63**	-588,031.44		-1977168.50**
				(0.040)	(0.037)	(0.536)		(0.021)
Inverse_SP	-11276845.00	-10509804.00		-13533291.00*	-12562647.00*		-10431762.00	-12749928.00*
	(0.108)	(0.133)		(0.058)	(0.071)		(0.136)	(0.070)
sh_turnover	-787,400.06		-814,614.63	-945,430.00		-873,547.69	-772,787.50	-961,646.31
	(0.311)		(0.293)	(0.225)		(0.252)	(0.320)	(0.217)
volatility		170,456.89**	338,596.19**		257,765.16**	379,235.50**	164,851.47**	262,885.28**
		(0.045)	(0.036)		(0.021)	(0.013)	(0.048)	(0.025)
Constant	1,577,184.00*	928,607.44	-108,757.73	18717220.00**	19513952.00**	6,118,177.00	1,269,850.38	22513352.00**
	(0.093)	(0.245)	(0.672)	(0.028)	(0.029)	(0.544)	(0.174)	(0.016)
Observations	58,560	58,560	58,560	58,560	58,560	58,560	58,560	58,560
R-squared	0.023	0.022	0.018	0.024	0.024	0.018	0.023	0.025

REFERENCES

Aggarwal, N., & Thomas, S. (2014). *The causal impact of algorithmic trading on market quality*. Retrieved from https://EconPapers.repec.org/RePEc:ind:igiwpp:2014-023

Anshuman, V. R., & Kalay, A. (1998). Market Making with Discrete Prices. *The Review of Financial Studies, 11*(1), 81-109.

Aşçıoğlu, A., Comerton-Forde, C., & McInish, T. H. (2007). Price Clustering on the Tokyo Stock Exchange. *42*(2), 289-301. doi:10.1111/j.1540-6288.2007.00172.x

Baker, H. K. (1996). Trading location and liquidity : an analysis of US dealer and agency markets for common stocks %J Financial markets, institutions & instruments. *5*(4).

Barclay, M. J. (2003). Price Discovery and Trading After Hours. *Review of Financial Studies, 16*(4), 1041-1073.

Bessembinder, H., Hao, J., & Zheng, K. (2019). Liquidity Provision Contracts and Market Quality: Evidence from the New York Stock Exchange. *The Review of Financial Studies, 33*(1), 44-74. doi:10.1093/rfs/hhz040 %J The Review of Financial Studies

Black, F. (1971). Toward a Fully Automated Stock Exchange, Part I. *Financial Analysts Journal, 27*(4), 28-35. doi:10.2469/faj.v27.n4.28

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-Frequency Trading and Price Discovery. *The Review of Financial Studies, 27*(8), 2267-2306. doi:10.1093/rfs/hhu032 %J The Review of Financial Studies

Chan, Y.-C. (2000). The price impact of trading on the stock exchange of Hong Kong. *Journal of Financial Markets, 3*(1), 1-16. doi:https://doi.org/10.1016/S1386-4181(99)00009-9

COPELAND, T. E., & GALAI, D. (1983). Information Effects on the Bid-Ask Spread. *38*(5), 1457-1469. doi:10.1111/j.1540-6261.1983.tb03834.x

Domowitz, I., Glen, J., & Madhavan, A. (2001). Liquidity, Volatility and Equity Trading Costs Across Countries and Over Time. *4*(2), 221-255. doi:10.1111/1468-2362.00072

EASLEY, D., & O'HARA, M. (1992). Time and the Process of Security Price Adjustment. *47*(2), 577-605. doi:10.1111/j.1540-6261.1992.tb04402.x

Foster, F. D., & Viswanathan, S. (2015). A Theory of the Interday Variations in Volume, Variance, and Trading Costs in Securities Markets. *The Review of Financial Studies, 3*(4), 593-624. doi:10.1093/rfs/3.4.593 %J The Review of Financial Studies

Foucault, T., Röell, A., & Sandås, P. (2015). Market Making with Costly Monitoring: An Analysis of the SOES Controversy. *The Review of Financial Studies, 16*(2), 345-384. doi:10.1093/rfs/hhg005 %J The Review of Financial Studies

French, K. R., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics, 17*(1), 5-26. doi:https://doi.org/10.1016/0304-405X(86)90004-8

Frino, A., Prodromou, T., Wang, G. H. K., Westerholm, P. J., & Zheng, H. (2017). An empirical analysis of algorithmic trading around earnings announcements. *Pacific-Basin Finance Journal, 45*, 34-51. doi:https://doi.org/10.1016/j.pacfin.2016.05.008

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics, 14*(1), 71-100. doi:https://doi.org/10.1016/0304-405X(85)90044-3

Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review, 70*(3), 393-408.

Heflin, F. L., Shaw, K. W., & Wild, J. J. (2005). Disclosure Policy and Market Liquidity: Impact of Depth Quotes and Order Sizes*. *22*(4), 829-865. doi:10.1506/eetm-falm-4kdd-9dt9

HENDERSHOTT, T., JONES, C. M., & MENKVELD, A. J. (2011). Does Algorithmic Trading Improve Liquidity? , *66*(1), 1-33. doi:10.1111/j.1540-6261.2010.01624.x

Kim, O., & Verrecchia, R. E. (1994). Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics, 17*(1), 41-67. doi:https://doi.org/10.1016/0165-4101(94)90004-3

KRINSKY, I., & LEE, J. (1996). Earnings Announcements and the Components of the Bid-Ask Spread. *51*(4), 1523-1535. doi:10.1111/j.1540-6261.1996.tb04078.x

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica, 53*(6), 1315-1335. doi:10.2307/1913210

Lee, C. M. C., Mucklow, B., & Ready, M. J. (2015). Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis. *The Review of Financial Studies, 6*(2), 345-374. doi:10.1093/rfs/6.2.345 %J The Review of Financial Studies

Lin, J.-C., Sanger, G. C., & Booth, G. G. (2015). Trade Size and Components of the Bid-Ask Spread. *The Review of Financial Studies, 8*(4), 1153-1183. doi:10.1093/rfs/8.4.1153 %J The Review of Financial Studies

Parkinson, M. (1980). The Extreme Value Method for Estimating the Variance of the Rate of Return. *The Journal of Business, 53*(1), 61-65.

Thomas, S. Y. H., & Michaely, R. (1988). Information Quality and Market Efficiency. *The Journal of Financial and Quantitative Analysis, 23*(1), 53-70. doi:10.2307/2331024

Venkatesh, P. C., & Chiang, R. (1986). Information Asymmetry and the Dealer's Bid-Ask Spread: A Case Study of Earnings and Dividend Announcements. *The Journal of Finance, 41*(5), 1089-1102. doi:10.2307/2328165

NAME

DATE OF BIRTH 03 May 1991

PLACE OF BIRTH Bangkok