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Algorithmic Trading in an Emerging Market: Empirical Study on the Stock Exchange of Thailand

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Abstract

This study examines the behaviors of algorithmic traders (ATs) in the Stock Exchange of Thailand (SET). I analyze the trade executions, order submissions and determinants of ATs orders which only accounts for a small proportion compared to human traders. I find that, despite low volume, ATs tend to follow the same notion of trading behaviors and order submissions as developed markets. ATs concentrate in the large-cap stocks and break up their large trade into multiple smaller trades. As the SET is dominated by human traders, ATs compete with humans on order submission. The evidence shows that it is more often to observe the ATs orders followed by human but not the other way around. I also find the evidence that ATs actively monitor market conditions. ATs almost never leave their orders unmatched but they make sure orders are matched within certain period, otherwise they will cancel them. ATs tend to use market orders when the order is small and chase after positive returns. If the order is large, past volume is high or exhibit high volatility, ATs is likely to use limit orders.

JEL Classification: G10, G19

Keywords: Algorithmic Trading, Emerging Market, Stock Exchange of Thailand

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Introduction

Algorithmic trading is a computerized-based order submission program with pre-condition strategies by the traders. Algorithmic traders (ATs) have speed advantage and lower monitoring cost relative to human traders. ATs can react quickly to news, change in market liquidity and volatility. With such advantages ATs can react faster than human in making trading decisions, reacting to changes in market conditions, and submitting orders. Various terms are used to refer to certain categories of algorithms such as low latency trading and high frequency trading. They are considered as a subset of ATs with distinct trading strategies because these are only possible with computer capabilities. Low latency trading is referred to trading strategies that react to market event in a fraction of one second depending on computer processing speed. High frequency trading (HFT) uses fast speed to submit a large number of orders into the market.

The arrival of machine trading has changed the financial market dramatically. Large proportion of daily trading volume in stock markets are now originated from AT (including HFT). The volume from ATs has grown rapidly in most developed markets. Hendershott and Riordan (2013) study 30 largest and most liquid stocks from Deutsche Bourse that contain all AT order submitted to DAX. They report that volume from ATs represent 52% of market order, and 64% of non-marketable limit order in the Deutsche Bourse. Hirschey (2013) finds that 40% of trades in the NASDAQ stock market are from HFT. The algorithmic trading on the Stock Exchange of Thailand (SET), however, is in its early stage. It has allowed trading software that can automatically submit order into the market since 2007. As of 2011 the maximum proportion of ATs activity relative to the entire market is 13.25% by number of trades, and 4% by volume. Despite the low volume, it’s interesting to investigate how ATs interact with human trading in term of liquidity providing and consuming given lower monitoring costs and speed advantage. This is different from other developed markets where ATs have been in the market for longer period and share sizable proportion of trading activity.

Previous studies show that ATs tend to use small size orders to hide their trading activities and minimize price impact of trades (Hendershott and Riordan (2013)). They tend to break down large orders into smaller ones which cause autocorrelation of trades. Consistent with the literatures, I find that ATs on the SET are most likely to use small-size orders. They break up a large order into smaller ones. In addition, ATs concentrate in the large-cap stocks which are more liquid since it is easy to hide their trades and has less price impact. Thus it is likely to observe clustered orders of the same order side (buy followed by buy, or sell followed by sell), rather than the order reversal. As the SET is dominated by human, ATs compete with humans with order submission. The evidence shows that it is more often to observe the ATs orders followed by human but not the other way around. However, I do not directly test whether ATs front run human traders or they simply act faster to change in market condition as ATs can react faster to incoming news and market conditions by submitting new orders or cancelling unmatched non-marketable limit orders depending on the pre-programmed algorithms. In addition to using small size orders, I find that when ATs use non-marketable limit orders, they are likely match faster than those of humans, or they will cancel them if not matched within certain period. The finding is also an evidence of AT actively monitoring market conditions.

Another important aspect of ATs' behavior is that how much ATs earn from providing and consuming liquidity. I study the short-term profitability of trades between ATs and humans. I find that ATs lose if they use market order to consume liquidity in all trade size category but they profit from offering liquidity to market in the small trades. However, ATs tend to even out as a liquidity provider since they make a loss in the large size trade. ATs order submission strategies depends on various conditions including liquidity volatility as well as order size. ATs tend to use market order when a stock experiences positive returns. Market order is less likely for large size orders, large-cap stocks and actively traded stock and experienced high volatility. ATs tend to use limit orders if they submit large-size orders, large-cap stocks, with stocks having been actively traded, and volatile. Last, ATs tend to cancel their orders for the large-side orders and when price is volatile. These results are in line with the previous findings that ATs tend to monitor market conditions when making submission strategy in order to hide their trading activity and reduce price impact of trade.

The remaining of the paper is organized as follows. Section 2 provides literature review in the algorithmic trading and high frequency trading. Section 3 describes the Stock Exchange of

Thailand and sample data. Section 4 discusses the interaction between ATs traders and human traders. Section 5 discusses the behavior of order submissions by ATs and humans. Section 6 is the analysis of determinants of ATs order submission. Section 7 is the conclusion.

Literatures Review

There is a growing finance literatures on the roles of algorithmic traders (ATs) and high frequency trading (HFT) in recent years. A number of papers analyze the roles and impact of ATs and HFTs in financial markets. Hasbrouck and Saar (2013) show that institutional investors use ATs for proprietary trading which aims to trade large quantity of shares with low market impact and trading cost. Brogaard, Hendershott, and Riordan (2013) study the aggressive and passive trading of HFTs in the price discovery.

The use of computer algorithms reduce monitoring costs of the market than human. Foucault, Roell, and Sandas (2003) study the equilibrium level of effort that liquidity suppliers should monitor the market. Foucault, Kadan and Kandel (2013) explain the behavior of traders by make/take liquidity cycle. Traders will take liquidity when it is cheap and supplying liquidity when it is expensive. Menkveld (2013) studies the role of HFTs as the new market makers. He examines HFT in Chi-X for European equity markets and show that they causes market fragmentation and lower spread. Market making by electronic system help reduce monitoring and search costs.

Identifying ATs orders is important but limited in previous studies. Some studies use proxies for AT activity. Hendershott, Jones, and Menkveld (2010) and Boehmer, Fong, Wu (2014) use the normalized number of electronic message traffic in NYSE as a proxy for ATs. Some studies obtain data from some brokerage firms. Engle, Russell, and Ferstenberg (2012) use execution data from Morgan Stanley to study the trade-offs between algorithm aggressiveness and the mean and dispersion of execution costs. Domowitz and Yegerman (2006) study execution cost of Investment Technology Group buy-side clients, and compare results from different algorithm provider. Some studies use comprehensive data on ATs in certain markets.

Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) study ATs in the foreign exchange markets on the electronic broking system (EBS) in 3 major currency pairs: euro-dollars, dollar-yen, euro-yen.

Choice of orders is one important component of trading in each transaction which varies by many factors. Two simplest choices are a market order and limit order. The market order is an order that can be executed immediately at the current market price which is considered as an aggressive order since it consumes liquidity by demanding immediate execution. The limit order is considered as passive order since the trading is possible only at its specified price. In addition, a limit order can be cancelled if it is not executed. The order aggressiveness of a limit order depends on the limit price and market stage. Ranaldo (2004) shows that market conditions including market depths on the same and opposite side, volatility, and order volumes affect the aggressiveness of order submission. Hirschey (2013) focus on HFT initiated buys and sells with marketable orders. He finds positive returns following HFTs aggressive buys and negative returns following HFTs aggressive sells. He shows that HFTs are better than others in anticipating order flows and they follow short-term price trend. Hendershott and Riordan (2013) show that ATs use small size orders and trade quickly when spread is narrow. ATs tend to be sensitive to human trades than the human traders are to ATs.

Upon monitoring the market condition, a trader can choose to leave his order to be hit by the opposite-side order (i.e. market order of the opposite direction), or cancel it and re-submit with more aggressive prices. Hasbrouck and Saar (2009) find that limit orders on the INET trading platform were cancelled within 2 seconds. Gai, Ye, and Yao (2013) find a dramatic in cancellation to execution ratio in the NASDAQ which may suggest quote stuffing behavior. ATs can exhibit different order submission behaviors from those of human traders due to lower monitoring cost and faster speed. This paper adds to the literatures by studying behaviors of ATs in an emerging markets which arrival of ATs is at its initial stages and share small fraction of market activities. The study offers an examination whether ATs exhibit the behavior of market monitoring, interaction between ATs and human traders and what are determinants of order submission strategy given the less activity than that in the developed markets. Empirical evidence of ATs can help traders and regulators understand advantages and disadvantages including the interactions between ATs and human traders in the financial markets.

Stock Exchange of Thailand and Algorithmic Trading

The Stock Exchange of Thailand (SET) is a pure order-driven electronic market. It operates under an automated order matching system. Trading sessions are divided into the morning session from 10:00 a.m. to 12:30 p.m. and afternoon session from 2:30 p.m. to 4:30 p.m[1]. SET uses two trading methods: call auction and continuous matching. The call auction determines the trade by finding the best price that maximizes trade volume and then executes accumulated buy and sell orders at the same time. The SET allows thirty minutes pre-opening sessions for traders to submit orders into the market to be executed by a call auction. This method is used to determine opening prices at the beginning of trading sessions and closing price at the market close.

The continuous trading method is used during two trading sessions when the SET is opened. It employs price-then-time priority matching method on the centralized limit order book. During the continuous trading, order arriving into the market is determined if it is executable at the current market price. For example if a buy order at a market price (or higher) arrives at the market, it will be matched with a sell order that has been on the limit order book immediately. The buy order can be a market order or a marketable limit order with the price equals to or higher than the ask price. Likewise for the sell side. If an arriving order is non-executable order, it will be waiting for future execution on the limit order book. From the matching mechanisms, I can determine if a trade is buyer-initiated or seller-initiated. SET displays limit order book information such as best bid-offer prices, depths (up to 5 levels), past trade volume and executions history of each day during the trading period to public traders. This is to ensure the level playing field for every trader who wish to observe the real-time market information.

SET employs the tick size rule for minimum price changes[2]. For example, if a stock price is from 5.00 Baht to less than 10.00 Baht, the tick size is 0.05 Baht. If a stock price is from 10.00 Baht to less than 25.00 Baht, then the tick size is 0.10 Baht. By rule, the spread varies from 0.4% to 1% depending on the trade price. This is different from some markets such as NYSE or NASDAQ that use decimal tick size. Sirodom et al (2008) document that tick sizes in the SET

[1] http://www.set.or.th/en/products/trading/equity/tradingsystem_p2.html
[2] http://www.set.or.th/en/products/trading/equity/tradingsystem_p5.html

are the strong binding constraints of bid-ask prices. The quoted spread appears to be at 1 tick size for 93% of all quotes. They argue that "the wider (narrower) spreads lead to higher (lower) depths because larger (smaller) tick size and time priority encourage (discourage) liquidity providers to display more (less) depth." Spread may not convey information regarding liquidity and adverse selection of a market maker as in the U.S. market. Thus I abstract away from using the spread as a measure of liquidity in this study.

SET has allowed trading software that can automatically submit order into the market since 2007. Currently brokers and their clients who wish to use algorithm trading software must get approval from the SET and have to trade via the special channel only. The approved strategies may include market making strategy, VWAP, TWAP, price inline, etc. However information about trading strategy is unobservable in the market as well as in my dataset. This paper provides empirical study on the roles of liquidity demander and suppliers of algorithmic traders (ATs) on monitoring and order submission behaviors in an emerging market where human traders dominate.

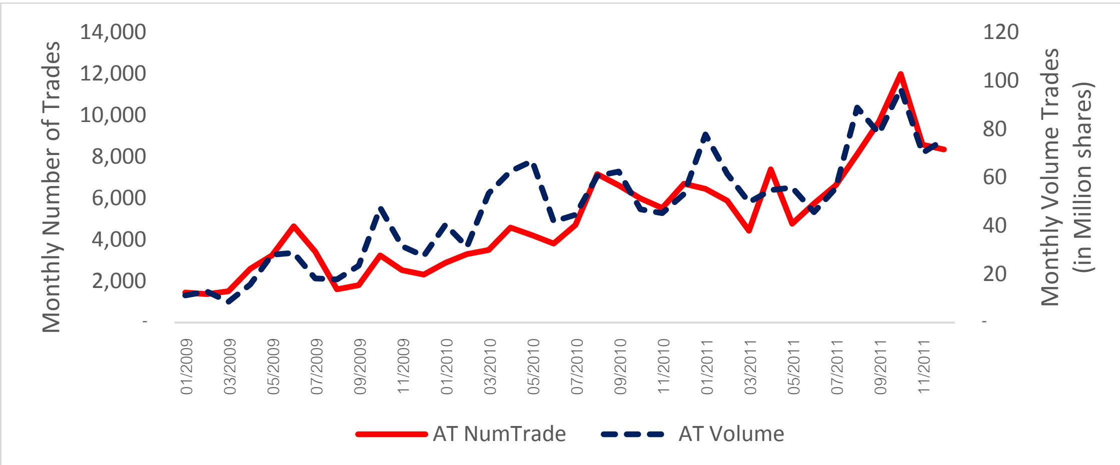
Data and Descriptive Statistics

I obtain the proprietary data set from by the Stock Exchange of Thailand (SET) covering the period from 5 January 2009 to 30 December 2011. The data come as order files and deal files (trade execution). This dataset is unique in that it includes all orders and executions taking place in a single market place while dataset in previous studies may include a fraction of trades in one market or limited transactions from some brokers. The order files from SET contain detailed information of every order submitted into the market. Specifically, each order contains the date and time of submission, order side (to buy or sell), order volume and price, and most importantly, the AT flag. The AT flag helps me distinguish precisely whether the orders are originated from AT or non-AT. This is important because it ensures that behavior of ATs is directly observed. This is different from other studies that rely on proxy of ATs activities (Hendershott et al (2013), Boehmer et al. (2014)). The deal files contain security symbol, date and time of each execution, buyer and seller information, trade price and volume. Since the SET is a pure order-driven market, no market maker operates in the market. Public orders are matched with each other. Non-marketable limit orders act as aggregated liquidity providers to match with marketable limit orders that act as liquidity consumers. Similar to Hirschey (2013) that studies trade patterns of aggressive buying and selling by HFTs on NASDAQ market, throughout the paper, I define the trade direction based on those who submits a market or marketable limit order, specifically, an order that initiates the trade as a buy or sell. Traders can choose to submit an order based on their pre-defined strategies, past information and tradeoff between risk of being pickoff and aggressiveness. In this study I exclude the trades in a call market since matching method is based on the auction mechanism. Only orders and trades originated during the continuous sessions are included. By matching these datasets, I am able to identify each transaction whether it is originated by human or computer program, whether it is a buying initiated or selling initiated trade, and whos act as a liquidity-provider or liquidity consumer.

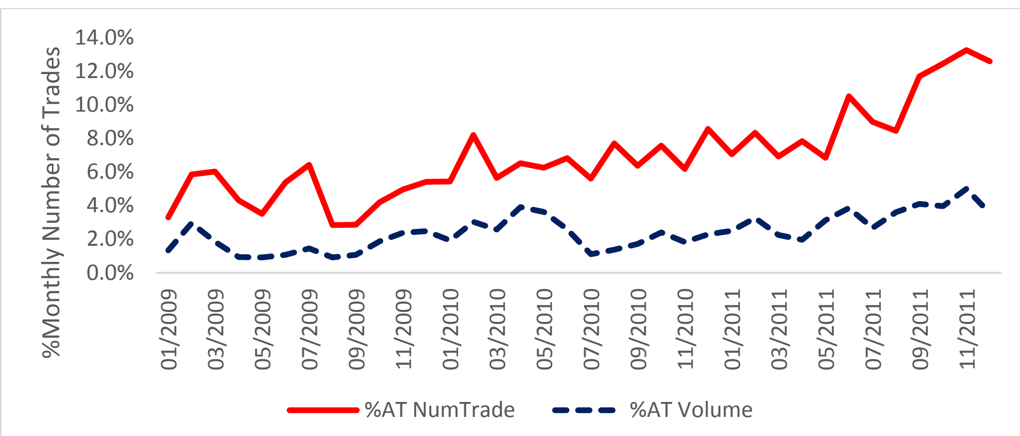
Figure 1 depicts the development of number of trades and volume of traders by ATs in every stock on the SET during my study period. Panel A plots the sum of raw number of trades and volume each month. Number of trades is on the left vertical axis and volume of trades (in million) is on the right. Trades from ATs are about 2,000 transactions per month at the inception and becomes 12,000 transactions per month in 2011. In term of volume, it is about 20 million shares per month and becomes 110 million shares at its peak in 2011. These show that trades from ATs are getting significantly higher over time. To compare with the overall market activity, I use above monthly trades measure divided by all trades in the market (i.e. both ATs and humans). The fraction of ATs was about 2% and increase to 12% by number of trades and 5% by volume. Panel B plots the proportion of the same AT activites relative to entire market. In 2009, AT volume started of at 2% of total trades of the entire market. The total number of trades from AT increases over time upto maximum at 4% while trade volume becomes 13.25% in 2011.

Figure 1. Number of Trades and Volumes from Algorithmic Traders in SET.

Panel A. AT Number of Trades and Volume



Panel B. AT Proportion of Number of Orders and Volume Relative to Market



The graphs present the development of number of trades and volumes of trades from algorithmic traders (ATs) on the SET from 05 January 2009 to 30 December 2011.

During my sample period, it is the early stage of the algorithmic trading in the SET which allows only institutional traders to submit order with AT. The proportion of AT orders is relatively small compared to orders submitted by human traders. As reported by SET[3], fraction

[3] Research Note, Volume 4, April 2011.

of trades from algorithm was 0.7% as of 2008. This is partly a limitation of my study since I must tradeoff between AT activities versus sample size in order to capture the evolution of ATs activity in the market. Compared to developed markets, ATs in the SET is at its initial stage with relatively small fraction of the entire market trading activity. However it has a merit to see the impact and behaviors are different when ATs account for a small proportion in the market because the developed markets already have high participation by ATs. In order to ensure sufficient liquidity, I restrict the sample to include only stocks that have AT trading activity every month throughout 3-year period. There are 57 stocks the meet my criteria which makes up 71.1% of total market capitalization. Table 1 report the summary statistics of the overall sample and three sample groups ranked by the market cap into small, medium, large group and the overall sample. Each group comprises 19 stocks. The descriptive statistics depict monotonic picture of trading activities. Small group consists of low price stocks at 12.7 Baht/share, 786 transactions per day or 15 million shares traded. Average trade size is about 12,400 shares per trade. Stocks in the medium size group has an average price at 34 Baht, 840 transactions per day with the 17 million shares traded per day. Stocks in the large size group have average trade prices at 109 Baht, more than 2000 transactions per day. Clearly trading activity concentrates in large cap stocks.

Table 1 Summary Statistics of Sample Stocks

Rank	N	Price	#Trade	Volume (Million shares)	Trade Size (Shares)	Market Cap. (Million Baht)
Small	19	12.27	786	15.38	12,389.84	14,775.81
Medium	19	34.17	840	17.06	9,539.55	37,763.40
Large	19	109.53	2,149	27.31	10,105.06	202,557.20
All	57	51.99	1,258	19.91	10,678.18	85,032.14

This table presents summary statistics of stock sample. To be included in the sample, the stocks must be traded by algorithm traders every month common stocks traded on the Stock Exchange of Thailand from 5 January 2009 to 30 December 2011. The samples are classified into 3 groups by market capitalization. Each group consists of 19 stocks. *Price* is the average daily close prices of the sample in a group. *#Trade* is the daily number of transaction traded per day per stock. *Volume* is the number of shares traded per day per stock in million shares. *Trade size* is average number of shares per transaction. *Market Cap* is the average market capitalization of a stock in the group calculated at the beginning of each year.

Analysis of Trade from Algorithimic and Human Traders

Trading behaviors and order submission can be broadly classified into liquidity demander and liqudity suppliers. Liquidity demanders require immediate execution by using a market order (or marketable limit orders) while liquidity suppliers offer the trade opportunity to other traders by using a non-marketable limit order with a limit price. Literatures find that liquidity demanders tend to breakup their orders into smaller piece to reduce price impact and which in turn their trading cost. In this study I also follow the above classification in algorithm and human traders.

Every trade consists of two sides: a buyer and a seller. I focus on orders that initiate the trades. I label a trade as AT if it is initiated by an algorithmic trader and HM if it is initiated by a human trader. First I analyze the trade by size categoy following Hendershott and Riordan (2013). I classify the order into 5 categories from 100 to 499, 400 to 999, 1000 to 4999, 5000 to 9999, and larger than 10,000 shares per trade[4]. Table 2 report fraction of the number of trades which are originated by ATs vs. human traders by trade-size categories. Panel A report the average frequency by number of trades while panel B reports volume weighted frequency. The first column is five trade size categories and the overall sample. Column 2 and 3 report trades originated from ATs and human. The last column shows the percent of trades in each size category. Even though the trades from ATs share a small fraction in the market, I find dinstinct pattern. Trades from AT concentrate in small categories. Two smallest groups account for 24% by transactions and 27% by volume. I also find that ATs rarely execute orders with large trade size. AT use larger trade-size than 10,000 shares account for 4% by number of trades and 2% by volume only. The findings are largely consistent with those of O'Hara, Yao, Ye (2012) and Hendershott and Riordan (2013). O'Hara et al show that HFT commonly use trades of 100 or fewer. Hendershott and Rirodan also document that 68% of volume trades of DAX30 stocks are fewer than 500 shares while only 23% of volume trades is more than 10,000 shares. The two smallest share the majority of trade transactions than human traders. They also find that fraction of ATs trade decrease as trade size increases. This can implies that ATs use small size trade to hide their activity (Bertsimars and Lo (1998)) and reduce trade impact. This is consistent with

[4] According to the trading rule in SET, each trade on the main board will take place as a lot consisting of 100 shares. Thus the possible number will be in the multiple of 100.

prior finding. It can be implied that, in the emerging market, ATs still follow similar notion as regards to trade size. Human traders, however, exhibit reversed pattern which partly may be due to ATs' choice of participation in small trades. However, unlike literatures that study in developed markets, the fraction of ATs is much smaller. I find no particular pattern in the unconditional frequency of trades with the transaction-weighted frequency. The diversed numbers indicates that overall trade executions in my sample are not clustered in any particular category. However, the volume-weighed is not relavant indication here as it gives more weights on the large trade transaction.

Table 2.Trade Participation by Size Category

Size Categories			
	Panel A. Transaction Weighted		
	AT	**Human**	**All**
0-499	12.44	87.58	19.21
500 - 999	11.15	88.85	9.25
1000 - 4999	7.97	92.03	27.96
5000 - 9999	6.85	93.15	10.93
10000+	3.88	96.12	32.65
ALL	**8.46**	**91.55**	**100.00**
	Panel B. Volume Weighted		
	AT	**Human**	**All**
0-499	13.99	86.03	0.13
500 - 999	12.89	87.11	0.19
1000 - 4999	9.50	90.50	1.94
5000 - 9999	8.01	91.99	2.29
10000+	2.04	97.96	95.46
ALL	**9.29**	**90.72**	**100.00**

This table reports the percent of trades originated by ATs and humans by size categories. Sample include 57 stocks that have trades from AT every month from 5 January 2009 to 30 December 2011 and trades must occur during the continuous trading period. Trades executed during the call auction periods are excluded. Panel A reports the perecent of trades by transaction weighted trade participation. Panel B reports the participation rate by volume-weighed trade participation. *AT* denotes the percent of trades originated by ATs. *Human* denotes trades originated by human traders. *All* denotes the percent of trades in each size category.

Next I examine correlations of trades conditional on the past trades. AT or human traders may attempt to monitor the market and form strategies to submit aggressive ordes (marketable limit orders) or passive orders (non-marketable limit orders). I follow the trade analysis as in Biais et al (1995) and Hendershott and Riordan (2013) to investigate behaviors of trades from ATs and humans. First I focus on the marketable orders that results in immediate execution in the market. In this study I classify traders into ATs and humans. Thus there are 4 possible combinations, specifically, AT following AT, human following AT, AT following human, and human following human. If there is any particular strategy of ATs to trade following other humans or vice versa, I should observe high probability of that trade sequence. In addition, I classify the trade by direction as a buyer-initiated or seller-initiated trade. Likewise, if ATs follow a specific strategy for their buys or sells, I should see high frequency on the conditional trade sequence. Table 3 reports conditional trades participation. Each cell in the table represent the frequency of seeing trades from human and ATs contingency on observing a buy or sell. Panel A reports the transaction weighted freuency and panel B reports the volume weighted frequency.

Obviously the largest trades frequency is from human traders trading among themselves. The first row shows that AT is less likely to follow another AT. The fraction of such behavior is 3.30% by trades and 0.85% by volume. Human trades following AT is 4.55% by trades and 2.54% by volume. On the other hand, AT trades following human traders accounts for 4.56% by trades, and 1.51% by volume. These findings is inconclusive that AT trades ahead of human traders or AT simply follows its own strategy but move faster given the same decision.

Considerring the trade direction, the evidence shows that buying-trades tend to be followed by another buy (sell) for both human traders and ATs. Trades reversal of buy (sell) to sell (buy) are less observed in all classification. This pattern exhibits autocorrelation of trades consistent with Hendershott and Riordan (2013),

To account for the fact that AT trades concentrate on the small sizes, I investigate the trade pattern conditional on past trade, and break down by size category. If I put the trade size conditional on traders and trade size categories, I should observe a diagonal effect where the highest probabilities lie on a diagonal. Hendershott and Riordan (2013) argue that if traders

Table 3 Trade Participation Conditional on Past Trade

Panel A. Transaction Weighted

Sequence of Order	**$Buy_{t-1}Buy_t$**	**$Buy_{t-1}Sell_t$**	**$Sell_{t-1}Buy_t$**	**$Sell_{t-1}Sell_t$**	**All**
$AT_{t-1}AT_t$	1.63	0.19	0.19	1.32	3.30
$AT_{t-1}HM_t$	1.80	0.69	0.63	1.44	4.55
$HM_{t-1}AT_t$	1.70	0.70	0.79	1.38	4.56
$HM_{t-1}HM_t$	41.23	6.30	6.27	33.79	87.59

Panel B. Volume Weighted

Sequence of Order	**$Buy_{t-1}Buy_t$**	**$Buy_{t-1}Sell_t$**	**$Sell_{t-1}Buy_t$**	**$Sell_{t-1}Sell_t$**	**All**
$AT_{t-1}AT_t$	0.39	0.03	0.03	0.41	0.86
$AT_{t-1}HM_t$	0.96	0.34	0.27	0.98	2.54
$HM_{t-1}AT_t$	0.52	0.24	0.22	0.53	1.51
$HM_{t-1}HM_t$	42.06	6.60	5.46	40.96	95.08

This table presents the percent of trade participation by sequence of trades. Each trade is classifited as *AT* if the trade is initiated by an algorithmic trader and *HM* if initiated by human trader. For example, $AT_{t-1}HM_t$ refers to a trade initated by algorithimic-initiated trade and followed by a human-initiated trade. Each trade is also classified by trade direction as a buy or sell. Column 2 to 5 report the percent of trade sequence conditional on traders, and trade direction. Last column reports an unconditional frequency of trade sequence.

Table 4 Trade Conditional on Past Trade and Size Classificaiton

Trade at t-1	Trade at t									
	AT1	**AT2**	**AT3**	**AT4**	**AT5**	**HM1**	**HM2**	**HM3**	**HM4**	**HM5**
AT1	**24.74**	**5.51**	6.88	1.65	1.73	**18.12**	7.36	18.31	5.71	11.32
AT2	**12.61**	**13.50**	**10.19**	2.35	2.40	15.61	7.23	18.84	6.15	13.34
AT3	**7.20**	**5.06**	**18.62**	**3.34**	**3.50**	13.44	6.46	19.47	7.07	16.49
AT4	5.33	3.22	**11.15**	**10.09**	**6.61**	10.91	5.84	19.89	8.10	21.39
AT5	3.63	2.16	7.19	**4.75**	**15.34**	8.22	4.71	17.48	8.27	**29.88**
HM1	2.49	0.86	1.60	0.47	0.63	**31.84**	**11.72**	26.78	7.62	16.03
HM2	2.31	0.87	1.62	0.51	0.71	**24.12**	**12.12**	**29.33**	9.04	19.45
HM3	1.77	0.79	1.63	0.53	0.80	17.45	**9.51**	**31.13**	**10.95**	25.44
HM4	1.26	0.68	1.67	0.59	0.93	12.55	7.52	**28.58**	**12.58**	**33.70**
HM5	0.79	0.42	1.20	0.54	1.16	7.95	5.02	21.22	**11.48**	**50.24**

This table reports conditional frequencies of trades based on the previous trader group and trade size. The first column indicates the past trade, and first row indicates the later trade. AT1 – AT5 indicate algorithmic-initiated trades and HM1 – HM5 indicate human-initiated trades with size-catogory 1 to 5 as in table 3. Three largest values in each column are highlighted.

exhibit trade correlations, diagonal effect in the table implies that traders of the same types tend to use the same size of trades. Results are reported in table 4.

I employ the same size categories as in past section. Each row sums to 100% and indicates the trader and size category of the past trade. Each column indicates who initates the current trade as well as trade size category. Three largest values in each column are highlighted. Interestingly I also find the diagonal effect in both ATs and human trade. For the smallest group of ATs, it is likely to observe small trades from ATs at 24.74% of the time. Chances of observing larger trades from ATs are much less. The next smallest AT trades reveal similar behaviors. If the past trade was from second smallest AT trade, chances of observing AT trades of the same size-category are 13.50%. Likewise for the remaining AT trade-size categories. Consistent with the previous findings, this indicates that ATs tend to use multiple small trades rather than one large trade. ATs breakup their orders to hide information and minimize the price impact of trade.

Now let's look at interaction of trade between ATs and humans. When the past trade is from smallest AT, it is likely to observe trades from human at smallest and moderate size at 18.12% and 18.31% of the time, respectively. When the past trade is from the second smallest

AT, it is likely to observe trades from human at smallest and moderate size at 18.84% and 15.61% of the time, respectively. The chances of observing human trades following ATs seem to cluster in the smallest, moderate and largest size categories. When observing past trades from humans, however, it is less likely to observe trades from ATs than those of human. The proportion of trades by human also exhibit the clustering of trades in the same size. It is arguable that ATs exhibit front running behavior to human traders. If that is the case, I should observe high frequency of past AT trades followed by human trades, but the by ATs themselves. Thus, my findings are inconclusive in this regards. There is weak evidence of pattern that AT trades first and followed by human as ATs in the 1-3 size categories exhibit relative large fraction of trades following another ATs as opposed to other human. ATs may simply follow its strategy to trade of the same size by breakup a large size order into the multiple smaller orders.

Correlation among the AT trading strategy: R-Measure

To investigate interaction of trades between ATs and human, I also test if there is correlation of trades among ATs and human trading strategy. Even though the trading in an exchange is an anonymous process. In the market where there are more human traders than ATs, algorithmic traders are likely to trade with human traders rather than among themselves. I adopt the approach by Chaboud, Hjalmarsson, Vega, and Chiquoine (2014) to examine my hypothesis. They argue that "at the extreme, if all computers used the same algorithms and had the exact same speed of execution, we would observe no trading volume among computer, while if they follow the algorithms that are no different from random orders, we would observe the trading between human and computer in the similar portion to trading among computers and computers". This section I examine the frequency at which ATs trade with each other compared with the benchmark model as proposed in Chaboud et al (2014)[5].

They propose that under the assumption of anonymous and random trading in the market, the probability of different type of traders should follow the random matching model which

[5] See Appendix 2 for the model discussion

yields the ratio $R = \frac{RC}{RH}$, where RC is the ratio of computer algorithm consuming liquidity from human traders relative to algorithmic traders, and RH is the ratio of human traders consuming liquidity from human traders relative to algorithmic traders, should be equal to one. In other words, computers should take liquidity from other humans in similar proportion that humans do from other humans. If R deviates from 1 it implies the deviation from random matching. I use the realized value of RC and RH as follows. $\widehat{RC} = \frac{Vol(HC)}{Vol(CC)}$ is the realized value of ATs consuming liquidity, where Vol(HC) is the volume of trades which humans are providing liquidity and computers are consuming liquidity, and Vol(CC) is the volume of trades which both liquidity provider and consumer are from computers algorithms. $\widehat{RH} = \frac{Vol(HH)}{Vol(CH)}$ is the realized value of humans consuming liquidity, where Vol(CH) is the volume of trades which computer are providing liquidity and humans are consuming liquidity, and Vol(HH) is the volume of traders which both liquidity provider and consumer are from human traders.

In addition, I also investigate the model conditional by trade directions. The random model also yield the ratio of buys as $R^B = \frac{RC^B}{RH^B}$ and sells as $R^S = \frac{RC^S}{RH^S}$ where the human and computer liquidity demanders initiate the buy and sell orders respectively. The R-ratio of the buy and sell is computed from the realized value accordingly as RH^B, $\widehat{RH^B} = \frac{Vol(HH^B)}{Vol(CH^B)}$; RH^S, $\widehat{RH^S} = \frac{Vol(HH^S)}{Vol(CH^S)}$ of RC^B, $\widehat{RC^B} = \frac{Vol(HC^B)}{Vol(CC^B)}$; RC^S, $\widehat{RC^S} = \frac{Vol(HC^S)}{Vol(CC^S)}$. The matching volumes are accumulated on a daily frequency. I use the natural log to convert the ratio to zero. Thus in order to test if R is equal to one, I test if the ln(R) is equal to zero instead.

Table 5 reports the mean value of natural logarithmic value of R ratio with daily frequency. The standard errors and t-statistics to test the null hypothesis that ln(R)=0 are also reported. From the table 5, the ln(R) of overall sample, buyer- and seller-initiated trades are significantly different from 0 or R is greaten than 1. These results indicates that ATs are more likely to trades with human rather than trading with each other as predicted by a random matching model. As discussed in Chabond et al (2014) that "we believe that the interpretation of R>1 as evidence of correlated AT strategies is the most plausible. … in the very first years of AT in this market, a fairly limited number of strategies were being implemented, with triangular arbitrage among the most prominent[6]". However, this finding is not an unambigous proof that trading strategies are the same across ATs nor they aim at trading with human. The main reason is that human traders dominate the market. ATs will be less likely to hit other ATs by nature due to higher proportion of trades from human. The last three columns reports the number of non-missing observations of RH and RC. Since the portion of trades from AT is significanly smaller than human trades, missing observations due to lack of ratio RC are excluded. The non-missing observations account for 70% for overall sample, 52% when classifying trades as AT-initiated buys and AT-initiated sells.

Table 5 Correlation of Trades with Benchmark Model

	ln(R)	**Std Err**	**t-stat**	**N**	**No. of positive**	**Fraction**
All	0.7387	0.0132	56.172	12027	8361	0.70
Buy	0.1348	0.0149	9.049	9264	4857	0.52
Sell	0.1090	0.0149	7.325	9063	4745	0.52

The table reports estimates of the relative degree to which ATs trade with each other compared to how much they trade with human traders based on the benchmark model. I report the logarithm of *R-ratio* of overall trades, buys and sells measured with daily frequency. The sample stock include 57 stocks from 5 January 2009 to 30 December 2011.

Analysis of Orders from Algorithimic and Human Traders

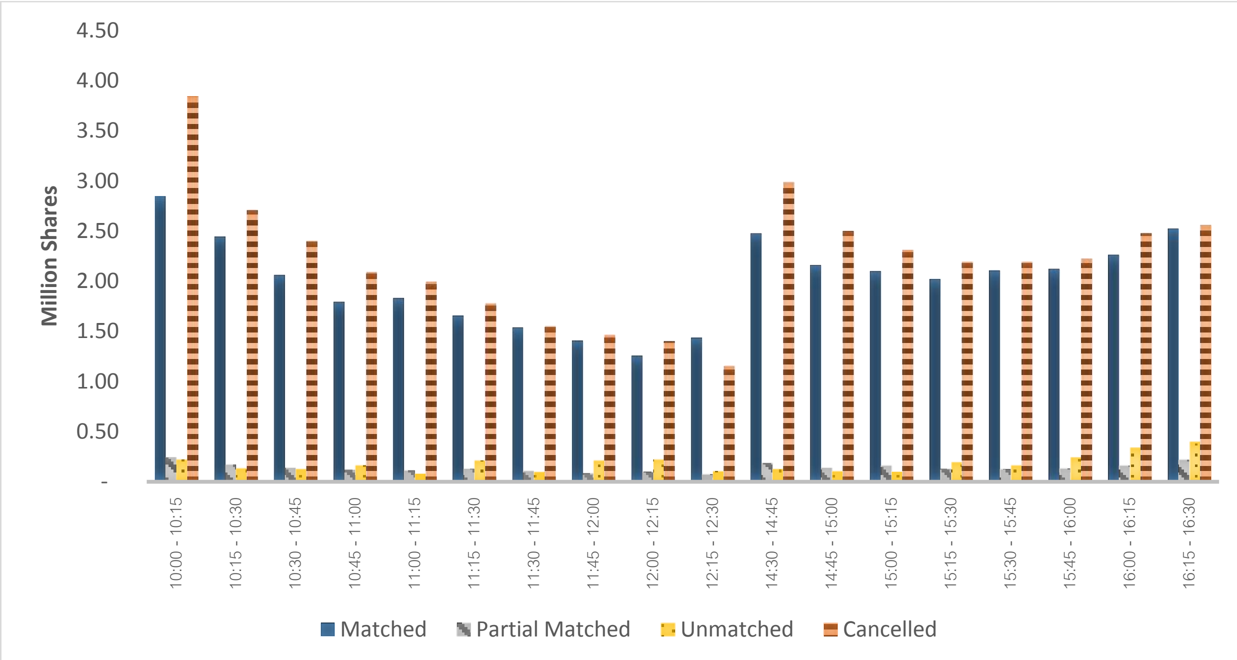
Up to this point, I study the behavior of ATs from the trades only. The executed trades are results of either aggressive market orders or passive limit orders. In order to understand ATs monitoring and order submission behaviors, I also extend the study by including all orders submitted by algorithms. Because some orders may not be executed if they submit passive orders with a limit price and they are on the unfavorable price move. They will not be hit by the opposite side orders throughout the day. This type of orders will become stale quotes posted in the market and do not appear in the deal files. SET only allow day order, any order, whole or part, that is not executed will be cancelled. Traders who submit a passive limit order can choose

[6] They study the algorithmic trading (AT) activity in the foreign exchange markets in major currencies.

to wait for execution or cancel it. If orders are not matched within certain period, traders may react by changing order to become more passive or aggressive. These orders exhibit the change in trader behavior caused by market monitoring.

I report summary statistics of all orders submitted by ATs and human into the orders that are matched, partially matched, unmatched, and cancelled, regardless of the aggressiveness and order direction (as buy or sell). I define orders as *matched* if the whole amount of orders are matched; *partially matched* if only a fraction of whole order volume are matched; *unmatched* if orders are matched with any other order until the end of day; and *cancelled* if orders are cancelled by the traders by the end of day. I compute the number of orders submitted by ATs to the market per day per stock. Figure 2 plots the proportion of each types of order throughout a day. It is obvious that the majority of orders include the orders that matched or cancelled. I find that volume from ATs exhibits W-shape pattern with the volume jumps significantly higher after the mid-day break. This may exhibit the new information arrival into the market. The graph also shows that cancelled volumes exceed matched volumes throughout the day while the partially matched and unmatched orders from algorithms are much smaller.

Figure 2. Order Submission by Time



This figure plots the order volume (in Million shares) submitted to the SET during a continuous market from 10:00 a.m. to 4:30 p.m. aggregated in each thirty-minute interval. Summation of volume are computed from the entire sample. Orders are classified into four categories. *Matched* orders if the whole amount of orders are matched; *Partially matched* if only a fraction of whole order volume are matched; *Unmatched* if orders are matched with any other order until the end of day; and *Cancelled* if orders are cancelled by the traders before the end of day.

Table 6 reports order categories sorted by market capitalization using the same sample as the table 1. The left panel show the orders submitted by AT and right shows the orders submitted by humans. Although ATs remain the minority in the market, orders submitted by algorithmic traders exhibit different patterns from that of humans. Majority of ATs orders results in either orders that are eventually matched or cancelled by algorithms. Daily number of matched orders by ATs is 47 orders per stock at the small size stocks, and 107 orders per stock. Daily number of matched orders total of 516,086 to 984,308 shares per stock. The order size tends to be small. ATs cancelled 38 – 88 orders with share volumes range from 629,883 to 1.1 million shares. Number of matched orders are somewhat higher than cancelled orders while the matched volume indicated the opposite. This may indicate that ATs break their orders into smaller size and submit them separately. Note that I do not distinguish market and limit orders at this point. The total matched orders can be the results of both. Unmatched and partially matched order, which are subsets of limit orders but are left on the market account for a small fraction of total AT orders. This evidence is important because it shows that ATs actively monitor their order submissions in the market.

A largest portion of orders from human traders are matched as well. Human traders, however, exhibit different behavior from ATs. The unmatched orders seem to account for a large amount of limit orders and they are left on the limit order book throughout the trading day. Since the SET only allows day orders, it seems that human traders simply submit a lot of orders away from the market or best quotes possibly, without monitoring the market as they do not even cancel the order until the end of day. This may partly be explained by Hirschey (2013) as he finds that non-HFT who provide liquidity do not update their quotes quick enough to update for information. Lastly, partially matched orders account for a few trades per day with about 1.8 million shares. These numbers seem small relative to other categories of human orders. All in all, human traders exhibit different submission behaviors.

Next I examine the order size as in Biais et al (1995) and Hendershott and Riordan (2013). I classify order into the buys and sells with various order sizes as in trade analysis. Table 7 report fractions of orders submitted by ATs and human traders. Panel A reports the fraction by transaction weighted and panel B is volume weighted. Each row sum to 100 percent. In panel A, the orders from AT in the smaller sizes have large fraction in the orders submission. The smallest group has the share of 9% by transaction, and 10% by volume. The fraction declines as the order size increases for both buy and sell orders. These results confirm the previous findings that ATs cluster their order in small-size categories.

Table 6. Descriptive Statistics of Orders Submission by Algorithmic and Human Traders

		AT Orders			Human Orders		
	MktCap	**#Trade**	**Volume**	**Order Size**	**#Trade**	**Volume**	**Order Size**
Matched	Small	47.45	594,638.63	12,532.09	573.69	30,072,810.37	52,419.64
	Medium	49.58	516,086.67	10,409.14	665.74	28,515,978.81	42,833.28
	Large	107.33	984,308.64	9,170.77	1,407.77	35,477,628.15	25,201.21
	All	74.46	737,156.66	9,899.77	882.50	31,355,994.77	35,531.02
Partially Matched	Small	2.73	138,902.69	50,854.89	5.95	1,908,408.93	320,675.35
	Medium	2.57	87,123.29	33,873.32	5.64	1,543,319.80	273,839.55
	Large	3.18	98,092.76	30,816.30	8.42	1,888,897.08	224,415.18
	All	2.92	101,854.85	34,913.97	6.72	1,782,451.40	265,243.42
Unmatched	Small	2.15	373,321.81	173,479.84	254.35	8,782,330.75	34,528.27
	Medium	1.95	141,697.01	72,720.85	334.85	9,948,104.92	29,709.34
	Large	2.09	120,844.96	57,733.62	729.87	9,772,807.02	13,389.71
	All	2.05	148,077.93	72,150.92	439.74	9,501,215.52	21,606.35
Cancelled	Small	38.54	716,399.59	18,586.48	235.38	16,981,483.55	72,144.68
	Medium	40.17	629,883.65	15,680.19	281.65	16,288,282.10	57,831.65
	Large	88.16	1,101,762.33	12,496.83	629.51	22,121,525.05	35,140.70
	All	60.94	855,088.11	14,031.96	382.23	18,464,341.21	48,306.85

This table reports descriptive statistics of orders submissions in the stock sample. Samples are the same as in table 1 and classified into 3 groups by market capitalization. Orders are classified into four categories. *Matched* orders if the whole amount of orders are matched; *Partially matched* if only a fraction of whole order volume are matched; *Unmatched* if orders are matched with any other order until the end of day; and *Cancelled* if orders are cancelled by the traders before the end of day sorted by market capitalization using the same sample as the table 1. The left panel show the orders submitted by AT and right shows the orders submitted by humans.

Table 7. Order Size Participation

Panel A. Transaction Weighted

Size Categories	AT		Human	
	Buy	Sell	Buy	Sell
0 - 499	5.32	3.61	50.61	40.50
500 - 999	4.57	3.46	48.67	43.35
1000 - 4999	3.23	2.65	48.81	45.32
5000 - 9999	3.00	2.79	47.09	47.14
10000+	1.67	1.84	46.16	50.34
All	3.56	2.87	48.27	45.33

Panel B. Volume Weighted

Size Categories	AT		Human	
	Buy	Sell	Buy	Sell
0 - 499	6.13	4.24	48.95	40.72
500 - 999	5.54	4.21	47.43	42.88
1000 - 4999	4.14	3.47	46.89	45.52
5000 - 9999	3.82	3.59	45.75	46.86
10000+	0.64	0.77	44.23	54.36
All	4.06	3.25	46.65	46.07

This table reports the order submission by size categories as in the previous tables. Numbers in column 2 to 5 indicate proportion of orders in each order-size category. Buy and sell orders are labeled as AT and Human. AT indicates that the order is submitted from algorithmic traders; HM indicates human traders. Buy and sell are reported directly in the dataset. Each row sums to 100%.

Hendershott and Riordan (2013) shows that orders are clustering and conditional on the previous orders. Same orders of similar types are likely to repeat. Since the SET consist of more human than ATs, I am likely to see the orders from human than computers. To investigate the source of orders, I classify four order types into buys or sell, with the size categories as in the previous tables. Table 8 reports the fraction of AT and human orders by transaction. Panel A and B shows the transaction weighted average frequency of AT, and human orders, respectively. Panel C shows the volume weighted average frequency of AT and human orders. Total frequency of ATs and human orders of the same row sum to 100%.

The results show that the order types that ATs use the most are market orders and cancelled orders. The cancelled orders is possible when ATs submit the limit order into the market but they are not executed immediately. Then algorithm revoke the orders. The previous findings show that the fraction of cancelled orders are larger than that of market orders and substantially larger than limit orders. This is consistent with the previous findings and indicate that ATs that submit limit orders tend to cancel orders often. However, from my dataset I am unable to identify whether the cancelled orders are revised to be more or less aggressive. ATs tend to cancel orders before the end of day while unmatched orders are tiny fraction of overall AT orders. The evidence reveals important behavior that is not observed from the trade analysis, which also confirms the hypothesis that ATs monitor the market.

Table 8 Order Submission Conditional on Past Order and Size Category

Panel A. AT Orders by *Transaction* Weighted Average

Size Category	Cancel Buy	Cancel Sell	Limit Buy	Limit Sell	Market Buy	Market Sell	Unmatched Buy	Unmatched Sell
0 – 499	2.21	1.46	0.97	0.69	2.16	1.48	0.01	0.01
500 – 999	1.93	1.44	0.99	0.75	1.66	1.28	0.01	0.02
1000 - 4999	1.39	1.10	0.80	0.68	1.04	0.86	0.01	0.01
5000 - 9999	1.25	1.13	0.91	0.90	0.84	0.77	0.03	0.03
10000+	0.64	0.66	0.69	0.81	0.34	0.36	0.02	0.02
All	1.48	1.15	0.87	0.77	1.21	0.95	0.02	0.02

Panel B. Human Orders by *Transaction* Weighted Average

Size Category	Cancel Buy	Cancel Sell	Limit Buy	Limit Sell	Market Buy	Market Sell	Unmatched Buy	Unmatched Sell
0 - 499	9.63	7.51	13.99	10.99	12.19	9.04	14.80	12.96
500 - 999	8.81	8.55	14.72	12.26	11.07	8.71	14.07	13.83
1000 - 4999	9.16	9.35	15.68	13.36	10.84	8.62	13.13	14.00
5000 - 9999	9.60	10.43	17.16	15.90	10.05	8.55	10.29	12.26
10000+	9.47	9.59	22.20	25.08	8.39	7.82	6.10	7.85
All	9.33	9.09	16.75	15.52	10.51	8.55	11.68	12.18

Panel C. AT Orders by *Volume* Weighted Average

Size Category	Cancel Buy	Cancel Sell	Limit Buy	Limit Sell	Market Buy	Market Sell	Unmatched Buy	Unmatched Sell
0 – 499	2.54	1.72	1.17	0.84	2.45	1.69	0.01	0.01
500 – 999	2.35	1.75	1.21	0.92	2.01	1.56	0.02	0.03
1000 - 4999	1.78	1.44	1.06	0.92	1.30	1.10	0.02	0.02
5000 - 9999	1.59	1.45	1.17	1.17	1.06	0.98	0.03	0.03
10000+	0.22	0.23	0.32	0.40	0.10	0.12	0.02	0.03
All	1.69	1.32	0.98	0.85	1.39	1.09	0.02	0.03

Panel D. Human Orders by *Volume* Weighted Average

Size Category	Cancel Buy	Cancel Sell	Limit Buy	Limit Sell	Market Buy	Market Sell	Unmatched Buy	Unmatched Sell
0 - 499	8.98	7.63	13.88	11.11	11.85	8.99	14.24	12.99
500 - 999	8.70	8.53	14.29	12.06	10.89	8.72	13.53	13.56
1000 - 4999	9.02	9.56	15.24	13.53	10.45	8.75	12.17	13.68
5000 - 9999	9.42	10.37	16.65	15.80	9.87	8.65	9.82	12.04
10000+	9.37	8.18	24.78	35.07	7.34	7.55	2.75	3.56
All	9.10	8.86	16.97	17.51	10.08	8.53	10.50	11.17

This table reports percent of orders submission conditional on past order and size categories. Orders from AT and human are classified as in the previous table into *cancelled, limit, market, unmatched* orders with order direction as buy and sell as reported directly in my dataset. Each row sums to 100 percent.

Passive Order Submission Analysis

The non-marketable limit orders are normally served as liquidity suppliers to the market. Traders can choose to leave the orders in the market as a stale quote or cancel the orders afterward. From table 8, fair amount of ATs non-marketable limit orders are later matched or cancelled. To better understand how ATs and human traders behave when they submit the non-marketable limit orders, I compute the time to match (TTM) and time to cancellation (TTC) of limit orders originated from ATs and humans. This measurement indicates how long the limit orders are sitting on the book and wait to be matched or cancelled. The time is measured in seconds but reported in the hour:minute:second format. To be consistent with other test, the results are reported by size category. However, I do not classify orders by aggressiveness. Table 9, panel A shows TTM and TTC of AT orders and panel B shows the same statistics of human orders. When ATs use a limit order to supply liquidity, it will be hit by the liquidity demander within 10 minutes. The smaller size orders tend to be hit faster than larger ones. For the TTC, it takes about 11 minutes which is slightly longer than the time to match. The TTC shows less distinct pattern regarding the order size but they are all longer than TTM. The patterns remain the same for the cases of buy and sell orders. This indicates that ATs monitor the market and make sure that if the order is not hit within a certain period, they will cancel it.

On the other hand, when human traders submit limit orders, average TTM is about twenty-eight minutes and TTC is fifty-five minutes. The waiting time until cancellation is almost one hour which is much longer than ATs. If breaking up by order size, the smaller size orders seem to wait longer to match. As the orders get larger, the TTMs are shorter. The time measure can be interpreted as indirect signal for aggressiveness and monitoring behavior of traders. Human traders tend to submit less (more) aggressive orders if they submit a small (large) order. This pattern is less prominent in the cancellation behavior. The average time to cancellation is roughly the same across the order size and direction, with the shortest TTC for largest order category buy order.

Table 9 Time to Match and Time to Cancel of Non-Marketable Limit Orders.

Panel A. AT Passive Order

	All		Buy Order		Sell Order	
Size Category	**TTM**	**TTC**	**TTM**	**TTC**	**TTM**	**TTC**
0 - 499	0:09:35	0:11:12	0:10:19	0:11:42	0:08:35	0:10:27
500 - 999	0:08:47	0:09:43	0:09:23	0:10:09	0:08:00	0:09:07
1000 - 4999	0:09:04	0:09:36	0:09:23	0:09:36	0:08:41	0:09:36
5000 - 9999	0:10:34	0:10:44	0:10:34	0:10:23	0:10:33	0:11:08
10000+	0:11:47	0:12:12	0:11:55	0:11:51	0:11:39	0:12:33
All	0:10:21	0:10:46	0:10:34	0:10:49	0:10:06	0:10:41

Panel B. Human Passive Order

	All		Buy Order		Sell Order	
Size Category	**TTM**	**TTC**	**TTM**	**TTC**	**TTM**	**TTC**
0 - 499	0:39:55	0:58:17	0:38:15	0:56:10	0:42:06	1:01:00
500 - 999	0:38:54	0:58:47	0:37:08	0:55:52	0:41:05	1:01:47
1000 - 4999	0:36:55	0:59:15	0:35:13	0:55:27	0:38:55	1:02:57
5000 - 9999	0:31:38	0:57:46	0:30:28	0:53:13	0:32:54	1:01:55
10000+	0:22:00	0:51:35	0:22:38	0:45:50	0:21:26	0:57:11
All	0:28:39	0:55:33	0:28:47	0:51:13	0:28:30	0:59:56

This table reports time horizon since order submission to execution and cancellation of non-marketable limit orders. Orders are classified by size categories and order sides. Panel A reports the orders submitted by algorithmic traders (ATs). Panel B reports orders submitted by human traders. TTM is the time to match and TTC is the time to cancellation. Both are calculated in seconds but reported in hour:minute:second format.

Profitability of Trades

This section estimates daily profits that traders earn from supplying and demanding liquidity. The dataset enables me to know the trading price and volume of each order originated from ATs and human traders. However I can observe only the trades but not their portfolio and its initial price. Thus I assume the all the AT and human orders represent the aggregate portfolio of the same groups. Following Brogaard (2010), I measure profits of trades by measuring daily net cash inflow from selling and outflow from buying in each trading, plus the remaining positions at the end of day by marking to market with closing price. Specifically,

$$Profit = \sum_{t=1}^{T} \left[SharesSold_{i,t} Price_{i,t} - SharesBought_{i,t} Price_{i,t} \right] + ClosePrice_{i,t} \sum_{t=1}^{T} \left[SharesBought_{i,t} - SharesSold_{i,t} \right]$$

Where $SharesSold_{i,t}$ is the number of share i on day t. $ShareBought_{i,t}$ is the number of shares i bought on day t. $Price_{i,t}$ is the trade price of share i being bought and sold on day t. $ClosePrice_{i,t}$ is the end of day price of stock i on day t. The first term represents the cashflow from buying and selling shares while the second term adjusts for end of day position of stocks by the closeing price. Sum of the two terms indicate short-term profit of traders when they trade on a given day. Summing up the profit for each stock on each day results in the total gain or loss for a trader on that day. I report the summation of profit for each day by the same trade-size categories as discussed above and average across day in the sample period.

The results are reported in Table 10. I calculate profits when traders use market orders and limit orders and then classify them by order size. Because there are two traders in this study, as one trader buy with a limit order, the other trader must sell with a market order and vice versa. Each row sums to zero. On average, when ATs use marketable orders, they all make losses of 66,334 Baht per day. When AT offer liquidity by using limit orders which later match, they are just even out. When breaking up to trade size categories, the results show that aggressive AT orders make losses in all size categories. For the smaller trades, ATs make a loss of about 15,622 Baht while the largest trades, AT make a loss of 152,317 Baht per day. However, AT limit orders are profitable for small trade sizes, except for the largest size where they lose to other traders. Human traders show different pictures. Given that they are majority in the market, their trades with both market and limit orders yield zero profit. However, when breaking up by trade size, the overal profit are dominated by the large trade size.

Table 10 Profitability from Trade

Size Category	AT				Human			
	Market Orders		Limit Orders		Market Orders		Limit Orders	
	profit	t-stat	profit	t-stat	profit	t-stat	profit	t-stat
Small	-15,626	-4.38	10,541	3.59	3,522	0.21	1,563	0.09
2	-17,522	-4.42	12,712	3.88	-76	0.00	4,885	0.22
3	-93,859	-5.26	40,712	2.57	-13,069	-0.14	66,215	0.65
4	-52,348	-3.82	16,661	1.34	-18,015	-0.30	53,703	0.85
Large	-152,317	-3.77	-80,233	-1.48	2,423,774	5.92	-2,191,224	-5.38
All	-66,334	-7.10	79	0.01	479,227	5.53	-412,971	-4.78

This table reports the short-term profitability of trades by measuring daily net cash inflow from selling and outflow from buying in each trading, plus the remaining positions at the end of day by marking to market with closing price. Specifically,

$$Profit = \sum_{t=1}^{T}\left[SharesSold_{i,t}Price_{i,t} - SharesBought_{i,t}Price_{i,t}\right] + ClosePrice_{i,t}\sum_{t=1}^{T}\left[SharesBought_{i,t} - SharesSold_{i,t}\right]$$

$SharesSold_{i,t}$ is the number of share *i* on day *t*. $ShareBought_{i,t}$ is the number of shares *i* bought on day *t*. $Price_{i,t}$ is the trade price of share *i* being bought and sold on day *t*. $ClosePrice_{i,t}$ is the end of day price of stock *i* on day *t*. I report the summation of profit for each day by the same trade-size categories.

Probit Regression on AT Order Submission

In this section I attempt to explain the order submission with several factors related to market condition. It is typical that we do not have any clear evidence what determine order submission strategies because this is confidential among traders. However, I argue that algorithmic traders monitor stock specific variables as determinants of order submission. Hendershott and Riordan (2013) show that ATs employs liquidity, volatility, and public information as determinant of order submission. I study three different types of order submission by ATs, specifically market order, limit order and cancel order. If an order initiated by AT is a market order which demand market liquidity, AT_{MKT}=1, otherwise 0. If an order is a limit order, AT_{LIM}=1, otherwise 0. If an order is cancelled, AT_{CCL}=1, otherwise 0. AT decision to submit orders or cancel orders may be due to various factors. I include order size, lagged returns, past volume, volatility and the market capitalization of the stock as factors that explain algorithm to submit a market, limit or cancel order.

I use lagged 15 minutes of stock return to control for trading strategy as momentum or contrarian. If ATs follow momentum (contrarian) strategy, it may use aggressive market (passive limit) order to follow positive return of the stock. Order size is included to examine how it affect ATs' order submission strategy. I use past 15-minute total volume trades and past return volatility as liquidity variables. Hirschey (2013) show that HFTs chases a short-term price trend. As the ATs are different from HFTs, I believe that 15 minutes are a good proxy to capture the trend following pattern in the algorithms.

I run the probit regression to estimate possibility of ATs submitting a market order, a limit order or cancel order based on various information. Table 11 reports the results of the probit regression. Column 2 reports the coefficient estimates for the market order together with the standard error and probability. Column 3 and 4 use the same stock-specific determinants in the case of limit orders and cancel orders. The probit results show that ATs are more likely to submit market orders when they observe past positive return. This is consistent with the hypothesis that ATs tend to be more aggressive than human. If the order size and past volume trade are large, ATs is less likely to use a market order. This is consistent with the prior finding. Hendershott and Riordan (2013) show that ATs rarely use large order size. If the return volatility is high, ATs may not need to be aggressive as the large price fluctuation may benefit less aggressive order by simply acting as a liquidity suppliers. Lastly ATs are less likely to use a market order with large stocks. The probit regression results of limit orders show that ATs tend to use a limit order when market is liquid and volatile, or they submit a large size order. In term of stock market size, the regression results suggest that ATs tend to use more limit and cancel orders than market orders which are consistent with my prior findings.

Hendershott and Riordan (2013) find ATs are more likely to initiate trades when liquidity is high. ATs liquidity demanding are negatively related to volatility and volume prior 15 minutes. For ATs that supply liquidity, they supply liquidity when liquidity is low. They have positively related to volatility. Finally ATs are more likely to cancel orders that are in opposite direction of recent index future returns, which make ATs avoid being adversely selected based on public information.

Table 11 Probit Regression Analysis

	Market			Limit			Cancel		
Variable	**Coeff.**	**stderr**	**p-value**	**Coeff.**	**stderr**	**p-value**	**Coeff.**	**stderr**	**p-value**
Intercept	2.722	0.015	0.000	-3.246	0.017	0.000	-1.492	0.015	0.000
$\text{Return}_{t-15,t-1}$	0.367	0.109	0.001	0.007	0.100	0.943	-0.464	0.094	0.000
Volume_{t}	-0.061	0.000	0.000	0.002	0.000	0.000	0.053	0.000	0.000
$\text{Volume}_{t-15,t-1}$	-0.064	0.000	0.000	0.099	0.000	0.000	-0.004	0.000	0.000
$\text{Volatality}_{t-15,t-1}$	-7.053	0.138	0.000	3.572	0.120	0.000	3.066	0.115	0.000
Market Cap_{i}	-0.071	0.001	0.000	0.044	0.001	0.000	0.039	0.001	0.000

This table reports the results from the probit regression analysis to estimate possibility of ATs submitting a market order, a limit order or cancel order. The header of table indicate order types. If an order initiated by AT is a market order which demand market liquidity, AT_{MKT}=1, otherwise 0. If an order is a limit order, AT_{LIM}=1, otherwise 0. If an order is cancelled, AT_{CCL}=1, otherwise 0. $Return_{t-15,t-1}$ is the logarithmic returns of 15-minute prior to the order submission; $Volume_t$ is the logarithmic value of order size; $Volume_{t-15,t-1}$ is the logarithmic of total order volume during the past 15 minutes before the submission time; $Volatility_{t-15,t-1}$ is standard deviation of past return in past 15 minute; MarketCap_i is the logarithmic value of market capitalization of stock *i* on day *t*.

Conclusion

Algorithmic traders (ATs) have gain interests from financial markets researchers. The arrival of algorithmic trading seems inevitable in financial markets. However, most studies are in the developed markets where significant proportion of trading activities are from ATs. Thus, I study the ATs order submission and trading behavior on the Stock Exchange of Thailand as a case of emerging market that ATs accounts for small proportion of activity. This study provides the first evidence of the ATs behavior and interaction between ATs and human traders. This is important to market regulators and participants in understanding the benefits and concerns that ATs caused to any stakeholder of financial markets.

Despite low volume, ATs tend to follow the same notion of trading and order submission strategy as in developed markets. ATs cluster their orders into small size and break up their large trade into multiple smaller trades. This behavior results in correlated trades on the same side of the market and same trade-size category, which shows that ATs tend to follow their pre-determined strategies rather than focusing on trading against other investors. The empirical evidences also show that ATs actively monitor market conditions. This is consistent with the fact that ATs have lower monitoring costs and faster speed to react the market condition. ATs almost never leave their orders unmatched but they make sure orders are matched within certain period, otherwise they will cancel them. ATs tend to use market orders when the order is small and chase after positive returns. If the order is large, past volume is high or exhibit high volatility, ATs is likely to use limit orders.

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Appendix

Appendix 1: List of Sample Stock in the Study.

ADVANC	ESSO	QH
AMATA	GLOW	RATCH
AOT	HANA	RCL
AP	HMPRO	SCB
BANPU	IRPC	SCC
BAY	ITD	SCCC
BBL	KBANK	STEC
BCP	KKP	TCAP
BEC	KSL	THAI
BECL	KTB	TICON
BGH	LH	TMB
BH	LPN	TOP
BIGC	MAKRO	TPC
CPALL	MCOT	TPIPL
CPF	MINT	TRUE
CPN	PS	TSTH
DELTA	PSL	TTA
DTAC	PTT	TTW
EGCO	PTTEP	TUF

Appendix 2: Benchmark model from Chaboud et al. (2014)

Given 2 types of traders in the market, computer (equivalent to algorithmic trader, AT, in this context) and human trader. I use the letter H to denote an order originated by human while C to denote an order originated by computer algorithm. Thus there are 4 possible combinations of trade, HH, HC, CH, CC. The first letter represents the liquidity demander, and second letter represents the liquidity supplier. From the benchmark model, the following equations hold. Let H_s denotes potential human liquidity supplier, H_d potential human liquidity demander, C_s potential computer liquidity supplier and C_d potential computer liquidity demander.

The probability of a computer providing liquidity to other traders is equal to

$$Prob(computer - supply) = \frac{C_s}{C_s + H_s} = \alpha_s$$

The probability of a computer consuming liquidity to other traders is equal to

$$Prob(computer - demand) = \frac{C_d}{C_d + H_d} = \alpha_d$$

Thus, the probability of a human providing and consuming liquidity will be $(1-\alpha_s)$ and $(1-\alpha_d)$ respectively. Assuming the events of trading between human and computer are independent, the probability of the trade pairs as a liquidity supplier and demander are as follows.

$$Prob(HH) = (1 - \alpha_s)(1 - \alpha_d)$$

$$Prob(HC) = (1 - \alpha_s)\alpha_d$$

$$Prob(CH) = \alpha_s(1 - \alpha_d)$$

$$Prob(CC) = \alpha_s\alpha_d$$

The probability above yields the ratios of

$$\frac{Prob(HH)}{Prob(CH)} = \frac{Prob(HC)}{Prob(CC)}$$

The first ratio is when a human trader is a liquidity taker, labeled as RH, while the second ratio is when computer is liquidity taker, labeled as RC. As described by Chaboud et al (2014), in a world with more human traders, both ratios should be greater than one that is computer is less likely to with human $Prob(HH) > Prob(CH)$ and $Prob(HC) > Prob(CC)$. However, under the assumption of random-matching model, the identity stated above should yield a ratio, R=RC/RH, equal to one. In other words, humans will take liquidity from other humans in similar proportion that computer take liquidity from other humans. If R deviates from 1 implies the deviation from random matching. If the ratio is greater than one, it refers that computers trade less among themselves but trade more with humans.