Trade execution during extreme market conditions:Institutions vs retail investors

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Abstract

This paper examines and compare trade execution performance as well as trading aggressiveness of retails and institutional investors in two different market conditions: normal days and extreme days (days where large price movement occurs). Generally, institutional investors tend to outperform retails in trading activities because they are known to possess higher sophistication level in designing investment strategy and information gathering capability. However, when traders need to response quickly to capture financial gain in extreme market condition, the advantages that institutions have over retails might not be that important when 'time to response' becomes matters to all investors. Since the ability to execute trade at better price will define trading performance, we compare price ratio of investors in both normal days and extreme days, and see which group of investors is better in trade execution when there is large price movements. We find institutional investors trade at relatively worse price than retails in extreme days.

To see how "extreme market condition" impact trade execution behavior of investors, we further investigated two aspects of trade aggressiveness: order initiation rates and order execution rates. We found evidence that, in general, both retail and institutional investors initiate their trades more aggressive in extreme market days than normal days. Similarly, the orders submitted by both investor groups are executed more in extreme days. Although both investor groups become more aggressive in extreme days, the level of aggressiveness is more pronounced in institutional investors for both execution rate and initiation rate point of view, except sell order during extreme market where retail investor is having slightly higher order initiation rate.

1. Introduction

Who is better in trade execution when there are large price movements, institutional or individual investors? When it comes to evaluate trading performance, we have seen literature heavily examine either trading performance during normal market condition or execution strategy during extreme market condition. In this study, we will focus on two aspects: trade execution performance and extreme market condition.

First of all, let us focus on first aspect, why do we focus on trade execution performance? Of course, not all the strategies are designed in the same fashion. But one common thing is that investment strategy associated with capital and asset allocation depends on individual macro view and specialization. However, strategy associated with executing trades depends on trader's decision-making skill in response to market and trade requirements that need to be fulfilled. Trade execution decision involves order price, order type and order size which are to be submitted. Making sure that submitted orders to get executed is quite challenging enough for traders even at normal market condition. Therefore, I believe it would be interesting to examine trade execution across investor types during extreme market conditions as traditional expectation towards each group of investors might be different in such condition.

Secondly, why extreme market condition is addressed? Under normal market condition, individual investors known as "noise traders" or "liquidity traders" suggested that they possess little or none investment knowledge and trade for non-information reasons such as behavioral bias and shift in risk aversion. On the other hand, institutional investors are considered as informed traders and being sophisticated

(Barber & Odean, 2008). They are equipped with advance facilities and they spend considerable effort to come up with not only optimal asset class allocation and investment strategies but also trade execution to earn superior investment performance. Jones and Lipson (1999) examined the investment style for orders initiation and execution costs for the orders submitted by institutions. Taking into account the market characteristics in which stocks are traded, they concluded that institutions actively supervise their strategies for order executions. Essentially, they require to best execute their orders without signaling the market of their intent from hard earned strategies. Therefore, institutional investors are expected to be able to deliver more impressive execution strategies than individual investors.

However, when market movements become extreme where absolute value of market price volatility is higher than normal level, trading performance of investors may demonstrate differently compared to normal market condition. Reason is that time horizon becomes matter to come up with optimal trading strategy when market movement is large. Normally when time is not one of the constraints, the more sophisticated group should be expected to outperform less than sophisticated ones. But when time becomes a constraint, advantages that institutions have over retail investors might not be much important due to the limited time to devote for material investment decision, which means quick response is required to maximize investment return from large price gap during extreme market period, otherwise traders may incur relatively worse execution price if they react slow. In addition, investors exhibit herd behavior[1]

[1] Herding behavior means, under certain circumstances, manager simply mimic the investment decisions of other managers, ignoring substantive private information. (Scharfstein & Stein, 1990)

when they are not certain to make profitable ideas based on prevailing market situation. Numerous literatures examine the existence of herding (Chang, Cheng, & Khorana, 2000; Chiang & Zheng, 2010; Christie & Huang, 1995; Demirer & Kutan, 2006; Lao & Singh, 2011). For example, Lao and Singh (2011) found a significant evidence that investors behavior of herding appear to be more pronounced when large market movements occurred in China and India. Not only individual investors may not behave in rational manner based on psychological bias, Dennis and Strickland (2002) documented that institutions act irrationally on large market movement days and suffer post-event underperformance. This can be explained that institutions tend to herd together with peers when they have short horizon to make decision since “an unprofitable decision is not as bad for reputation when others make the same mistake”. (Froot, Scharfstein, & Stein, 1992; Scharfstein & Stein, 1990)

Moreover, institutions attempt to change trade size in accordance with market situation. Barclay and Warner (1993) noted that institutions generally trade medium size in order to prevent not only revealing of information but also price impact exposure. If informed traders are likely to place larger order size to maximize the profit from short-lived information(Easley & O'hara, 1987), during extreme market conditions, institutions are likely to place larger order size for the purpose of maximizing profit from large market movement within short horizons. Consequently, placing larger order size bears higher implicit cost (i.e., price impact cost or opportunity cost) which leads to higher total trading costs.

To know whether the old belief regarding institutions performance over individual investors is still applicable when time become constraint, it is worth to examine trading performance of investors during large price volatility. Under extreme market condition, one could argue that individual investors are those who will display the most intense response to large price movement because they are less-informed noise traders who have a short-term speculative investment perspective and are prone to get the influence of psychological biases (Li & Wang, 2010). Conversely, one could argue that transient institutional investors who trade actively to maximize short-term profit (Bushee, 2001) may decide to react strongly as they anticipate many others also to be aggressive during large price gap and, fear to gain very low profit if they remain slow.

Having controversial conjecture, Dennis and Strickland (2002) empirically investigate whether institutions or individuals are more sensitive during volatile market. They conclude that institutions are more strongly react than individual in volatile market. This is consistent with the notion that the assessment on performance of fund managers are more often and particular evaluation period mostly focus in short-term performance, hence they have more incentive to react aggressively when large market movement occurs. However, this evidence was found in US markets and whether this observation can be deductive in emerging market such as Thailand inconclusive evidence. Additional reason of investigating Thai stock market is because, Thai market is pure order driven market which is dominated by retail investors. Unlike hybrid or quote driven market where institutions dominate the market, this evidence shed more light on the dynamics of aggregate retail investors in the pure order driven market during large price movements.

Keim and Madhavan (1997) conclude that differences in costs across institutions may indicate real variation in trading performance. Additionally, Jones and

Lipson (1999) document that institutions actively manage execution strategies. Motivated by these studies, this study extends the scope by examining trade execution and trading costs in different market condition where stock price is highly volatile (i.e., 3% or more). Taken together, we aim to conclude two main research questions: (i) who is better in trade execution when there is large price movement? (ii) how 'time constraint' impact trade execution behavior of investors during extreme market?

To the best of my knowledge, this paper gives contribution in following ways. First, we extend the existing scope of literatures on trade execution performance across investor types by adding a proxy of 'time constraint' into the study. Due to having superior resources and sophistication strategies, institutional investors are believed to outperform individual investors when market is at normal level. During extreme market condition, however, fast decision making plays a crucial role in determining execution performance because of large opportunity cost exposure if traders delay their execution.

In general, institutional investors are considered to possess not only higher level of sophisticated trading strategy but also information gathering capability. Thus, as second contribution, this research will provide an evidence on whether institutional investors lose these advantages when fast decision making becomes an important factor to trade under 'extreme market' environment.

Third, this study contributes to existing research on how 'time constraint' impact order submission aggressiveness level across investor types when facing with abnormally high opportunity cost.

2. Literature Review and Hypothesis Development

2.1 Literature Review

Many studies attempt to analyze behavior and trading costs among different investor groups and identify the better performer. However, very little to none focus in extreme market movement condition. Before reviewing literatures regarding this question, why extreme market condition matters to trading behavior is better to be observed first.

2.1.1 Investors' behavior

(Thaler & Shefrin, 1981; Tversky & Kahneman, 1992) explore how decision markers behave differently in the situation of high uncertainty. This issue led subsequent works to examine investors trading behavior with respect to various market conditions. (Choe, Kho, & Stulz, 2005) explore the relationship of trading behavior as well as foreign investors' impact during crisis in Korea market. They focus the period of 1997 Korean economic crisis using intraday data and examine the period before Korean crisis separately as well. They found sufficient evidence of positive feedback[2] trading and herding behavior of foreign investors before the crisis. Their finding suggests that there is no evidence that trades from foreign investor had destabilizing effect on the Korean stock market when market turmoil.

One of the studies related to market turmoil on individual investors is carried out by (Hoffmann, Post, & Pennings, 2013) in their paper named "Individual investor perceptions and behavior during the financial crisis". As the name suggested, they

[2] Positive feedback trading is foreign investors purchase (sell) more stocks on days following a raise (decline) in the market as a whole and they purchase (sell) stocks which outperformed (underperformed) the market over the previous day. (Choe, Kho, & Stulz, 1999)

examined how individual investors perceive and behave during 2008-2009 financial crisis by measuring the *variables* of expectation on market return, perceptions on risk and risk tolerance. Coupling with information obtained from brokerage records regarding investors' trading and their risk-taking behavior, they documented that retail investors continue to actively trade and they appear not to take steps to make their investment portfolio less risky during the crisis.

2.1.2 Investor behavior during extreme market

A large group of literatures examine investor behavior across different countries during high market stress and increasing uncertainty. However, only a little literature has received attention on behavior across different investors group during extreme market condition. One of them is researched by Dennis and Strickland (2002) in their paper called "Who blinks in Volatile markets, Individuals or Institutions?". They addressed the answers by examining the return of stocks and the ownership structure during volatile days, defined as when the absolute value of market return was larger than two percent or more. They have found following interesting conclusions.

First, they test whether larger institutional ownership are observed to have more negative for stock returns, based on the belief that institutions sell more than retails when large market decline occurs. After controlling for risk, they find that institutional ownership proportion in the firms has inverse relationship with stock returns when large market price drop happens. Similarly, they observe the same results on days when there is large market price increase. In particular, stocks with greater proportion of institutional ownership exhibits higher return than those with lower ownership proportion during large market movements.

Second, as proportion of institutional ownership was relevant in extreme market condition, they further explore types of institutional ownership and analyze their impact on firm's abnormal return. The results indicated that ownership of mutual funds, endowments and pension funds have positive relation to the abnormal return on raising days and vice versa. They noted that it is consistent with theoretical explanation ((Scharfstein & Stein, 1990) in such a way that the performance of fund managers is subject to evaluate more frequent.

Third, they test how proportion of institutional ownership relate to abnormal share turnover on volatile days and the evidence exhibits they have positive relationship. Lastly, they continue to explore the abnormal return after volatile days, and it was found positive for large institutional ownership stocks and negative for lower institutional ownership stocks.

2.1.3 Trade Execution

To know the better performed investors group during extreme market, We compared how well they execute trading strategies in accordance with prevailing market condition in a given short horizon period. Two determinants of execution strategy are order placement strategy and trading cost incurred to execute that strategy. Prior market microstructure literature often explains investor's order placement strategy by analyzing the trade-off between advantage and disadvantages of using limit order and market order. When traders place the orders, they choose to use either market or limit orders based on various factors as time constraint and objectives, etc.

Harris and Hasbrouck (1996) explore order submission strategy in their paper named "Market vs Limit order", which conduct research on NYSE SuperDOT traders during November 1990 to January 1991. They found that the price of limit orders and trade size affect the execution rate probability of limit orders. Orders which are priced are more aggressively and smaller size tends to have higher execution probability.

In the literature which study limit order book market, two models can be observed: liquidity based model and information based model (Bloomfield, O'hara, & Saar, 2005). (Cao, Hansch, & Wang, 2008) note that *liquidity based* model predicts limit orders become more favorable as the inside spread raises whereas market orders become less attractive. In *information based model*, informed trader actively use market orders to gain financial benefit from short-live information, however, recent evidence suggests that informed traders also submit limit orders. Bloomfield et al. (2005) investigate trader's decision between market and limit order by conducting market simulation. In their experiment, informed traders initiate trading with market order to capture large price gap which deviate from the true value of asset.

Ekkayokkaya, Jirajaroenying, and Wolff (2020) examined and compared trading execution performance across different investor types using the data from Stock Exchange of Thailand during 2003 to 2013. By comparing average buying and selling executed price, he found that aggregate retail investors perform better than local and foreign institutions in trading local stocks in such a way that retail investors seems to outperform the other groups in buying and selling stocks with any sizes.

2.1.4 Trade Execution during high volatility

Foucault (1999) uses dynamic equilibrium model to examine limit order submission rate when true value of volatility is larger. When high volatility is increased, it is likely that limit orders by traders will become mispriced because traders are not able to cancel their limit orders. This expose the risk of being picked off which makes traders to place their limit orders in less aggressive price. As a result, the spread will be larger, hence market orders get to be more expensive and reduce their proportion in the order circulation.

Ahn, Bae, and Chan (2001) is another work that explore how transitory volatility impact the combination between limit orders and markets order in Stock Exchange of Hong Kong which is pure order-driven market. The authors conclude that when transitory volatility originate from the ask side, investors will place limit sell orders more than market sell orders and vice versa.

In summary, execution strategy has been investigated by the considerable amount of studies. Studies on such areas for institutional and individual investors during large market movements and explore who execute better are, however, underway. What we know is institutional investors possess higher sophistication level in designing investment strategy and information gathering capability. What we want to know from this study is whether such advantages still effective and help institutions gain financial benefits over retails when fast execution becomes matter in highly volatile markets.

2.2 Hypothesis Development

In this section, we would like to propose hypothesis on trading performance that one would expect to observe from institutional investors and individual investors. While prior papers portray individual investors as “noise trader”, recent studies suggest that retail investors execute at more favorable price than institutional investors domiciled in the same market (Fong, Gallagher, & Lee, 2014; Kelley & Tetlock, 2013). However, most of the studies take place during the market is at normal level. When there is a large price movement, time becomes matter which might render institutional advantages over retail investors less effective. If they keep following their initial trade execution strategies due to having less time to come up with optimal strategy, it might lead to incur high opportunity cost because initial strategies are meant to be applied during normal market condition. Moreover, institutions have to fulfill certain investment requirements within given period while spending effort to earn superior return for their investors. As concluded by Easley and O'hara (1987), assuming institution investors as informed traders, they are likely to place large order size to maximize the profit from short-lived information. Because of large investment position and fast execution become matters, traded price to get orders executed from such large trade size will be exacerbated in highly volatile market. Taken together, if time constraint makes institutional investors advantages become faded, we believe aggregate institutional investors should obviously be at a disadvantage when trading against aggregate retail investors whose trades are more likely to get executed due to smaller trade size. Therefore, our first hypothesis is:

Hypothesis 1.1: Institutional investors execute their trades at worse price during extreme market period than that of normal market period

Hypothesis 1.2: Institutional investors execute their trades at worse price than retail investors during extreme market period

During extreme market condition, stock price deviate from its true value which attract transient institutional investors[3]. (Aitken, Brown, & Wee, 2007; Hasbrouck & Saar, 2002; Wald & Horrigan, 2005) show that investors, in general, reduce the usage of limit orders relative to market orders when the volatility gets higher. Otherwise they would suffer un-execution risk by using limit orders while others may derive benefits from large price gap by using market orders. Assuming institutional investors are informed traders, they favor market orders and actively submit them to profit from short-lived information (Glosten, 1994; Rock, 1996; Seppi, 1997). Therefore, they are expected to act aggressively in placing the orders during extreme market. Besides we believe institutional investors become even more aggressive than trading in normal market condition because the possible gain from large price gap may help them full fill their investment requirements in given period. Therefore, this leads to our second and third hypotheses:

Hypothesis 2.1: Institutional investors are more aggressive in order submission during extreme market period than that of normal market period

Hypothesis 2.2: Institutional investors are more aggressive in order submission than retail investors during extreme market period

[3] who trade actively to maximize short-term profit

3. Data and Methodology

3.1 Institutional Background

The Stock Exchange of Thailand (SET) is pure order driven market without having any designated market marker. Trading on SET is operated on a fully computerized trading system and liquidity is provided by traders who submit limit orders. During trading period, the orders are matched according to price and then arrival-time priority. Both market order and limit order are allowed to use on SET and all orders become expired by the end of the trading day. SET use *'call market matching'* to determine the opening price for morning and afternoon sessions, and closing price. The unique feature of order driven market is transparency. In such a way that last transaction price, traded volume, five best bid and ask prices with corresponding depths of the order book are disclosed to the public in real time. The identity of the trader remains anonymous to the public.

3.2 Data

The intra-day transaction data examined in this study are proprietary and provided by the SET for sample period of January 2008 to December 2017 which are the most updated dataset. The data contains complete information of intra-day transactions such date, trade submitted and executed time, price, order and trade size, security symbol and investor type flag. Each order time-stamped as of the order arrival time at the exchange and as of the order executed time, are compiled in the data. Further, we are able to identify the type of investor who initiate the order as well as corresponding counterparty orders. SET identify investors into three categories: individual investors, institutional investors, and foreign investors. To examine our central research question of this study, we will focus on two type of investors:

individual investors and institutional investors (including foreign investors). In Thailand, majority of foreign investors are institutional investors. Regardless of other differences between domestic and foreign institutional investors, they are equipped with quite similar sophistication level when compared to retail investors. In this study, we aim to investigate the advantages that institutions possess over retails when market price become extreme. Since we analyze trading performance between retail and institutional investors, we include "foreign investors" as "institutions". Most importantly, the data contains useful information for our experiment (i.e. unique order identification) by which we can find the executed and unfilled portion of specific orders.

3.2.1 Definition of normal days and extreme days

Generally speaking, there are approximately 250 total trading days in a year. 99^{th} and 1^{st} percentile should represent these few days when market move extremely high and extremely low. Therefore, we use 99^{th} and 1^{st} percentile to represent the extreme market condition. Out of total trading days, normal days are days when material information is not incorporated with market movements. And extreme days are days when the movement of market become extremely high or low. Normal days in this study are defined as trading days when the returns of SET100 constituent stocks are between 60^{th} and 40^{th} percentile which is approximately +/-1% of the return. The extreme (or event) days are defined as trading days when the returns of SET100 constituent stocks are at or higher than 99^{th} percentile and at or lower than 1th percentile which are approximately +/- 3.5% of the returns. During the sampling period, 96,826 observations are as total trading days. Among them, 14,808 and 1,729 observations are classified as normal days and extreme days respectively. **Table 1** demonstrates the summary statistics of rate of returns which we use to classify extreme days and normal days according to the criteria. Note that we pull the last price data from bloomberg and apply log return method *(log(current price/last price))* to compute the rate of return. Because this method is widely used in finance as it assumes returns are compounded continuously rather than across sub-periods because the stock market is changing overtime.

Table 1: Summary statistics for rate of return during extreme days and normal days

	Mean	**Median**	**SD**	**Min**	**Max**	**N**
Return on extreme days	-0.068%	-4.546%	8.877%	-30.187%	26.304%	1729
Return on normal days	-0.015%	0.000%	0.207%	-0.643%	0.599%	14808

Since institutions, in general, are trading largely in liquid and large-cap stocks (Bessembinder & Kaufman, 1997; Keim & Madhavan, 1997), we use SET100 stocks as main criteria as they represent approximately 80% of trading volume and market capitalization of the stock exchange. There are total 224 stocks are listed in SET100 throughout our sampling period of 10 years and 41 stocks out of them are consistently listed every year during the period. The objective of the study is not only to observe trading activity during extreme days but to make comparison with that of normal days. Therefore, we pick only the constituent stocks that are continuously listed on SET100 during our 10-year sample period. This bring the number of observed stocks to 41.

3.3 Methodology

3.3.1 Price Ratio (H1)

To compare trading performance, we follow price ratio method reported in Choe et al. (2005) which compare average trading price for buy and sell. Before we investigate inferior trading price among different investors during extreme market, we need to separate buy orders and sell orders of the event days, and to assign them with each investor type who made such order.

We first compute the volume-weighted average price (hereafter VWAP) using all the trades on each day during sample period. Suppose P_i^{dt} as the price of stock *i* on day *d* for trade *t*, and V_i^{dt} as the number of shares of the trade for stock *i* on day *d* for trade *t*. One order represents one trade *t*. Hence, VWAP for all trades on that day:

$$VWAP_i^d = \sum_t \frac{P_i^{dt} V_i^{dt}}{V_i^{dt}} \text{ (equation 1)}$$

We then calculate the VWAP separately for all buy and sale trades for different investor type *j*:

$$VWAP_{i,j}^d = \sum_t \frac{P_{i,j}^{dt} V_{i,j}^{dt}}{V_{i,j}^{dt}} \text{ (equation 2)}$$

Finally, we compute the price ratio of investors type *j* for stock *i* on day *d* by dividing equation (1) by equation (2). For example, price ratio for each investor *j* can be computed and interpreted as follow:

$$Price\ ratio\ {}_{i,j}^{d} = \frac{VWAP_{i,j}^d}{VWAP_i^d} \times 100 \text{ (equation 3)}$$

To measure how one group of investors is worse off relative to the other type, we will investigate on the difference in price ratio between investors groups. For each stock traded on each trading day, price ratio difference will be computed as:

$$Price\ ratio^{d}_{i,(re-ins)} = Price\ ratio^{d}_{i,re} - Price\ ratio^{d}_{i,ins}$$

To test whether the price ratio difference is statistically difference from zero, we shall apply T-statistic where the null hypothesis H_0: Price ratio $^{re\text{-}ins}$ =0.

<u>Trade price determinants</u>

In this section, borrowing from Choe et al. (2005), we investigate whether the difference in trading price between investors can be explained by different market conditions. The dependent variables are defined as daily price ratio of each investor group for each stock. We use dummy variable as variable of interest representing *dumExtreme* which is equal to 1 if the market is during extreme condition, and 0 if the market is during normal condition. Largely referring to the existing research of (Choe et al., 2005; Ekkayokkaya et al., 2020), we then control for stock characteristics and trade-related characteristic which are meant to affect trading price. The set of controlling variables are defined as follow:

(i) Stock characteristics:

− *lsize* = log of market capitalization on the previous day

− *pe* = price to earnings on the previous day

If one investor group is at a disadvantage when trading stocks during extreme market, it can be argued that information asymmetry become more important. It is often argued that information asymmetries fall when the firm gets larger. Moreover, firms with better growth opportunities may have more information asymmetries as it is harder to evaluate intangible assets. Hence, daily stock's market capitalization and P/E ratio are used as proxies for information asymmetry in term of current asset in place and future growth option respectively which are expected to affect investor trading performance. The degree of information asymmetry will be less with large market capitalization and low P/E ratio.

(ii) Trade-related characteristics:

− *avgturn* = average of previous 20 daily turnover ratio ($\frac{daily\ trading\ volume}{Total\ share\ of\ outstanding}$) x 100

− *avgvol* = average of previous 20 daily volatilities ($\frac{highest\ price - lowest\ price}{highest\ price + lowest\ price}$) x 100

These variables are used as proxies for stock asymmetry and liquidity which are known to have impact on trade price. Perhaps the difference in trading performance between investors could be explained by low trading volume stock and stock with greater asymmetry. The regression model in our test are as below:

$$Price\ ratio_{i,ins}^{d} = \beta_0 + \beta_1 dumExtreme_i^d + \beta_2 lsize_i^d + \beta_3\, pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d$$

The regressions are conducted separately for buy and sell price ratio of each investor type *j* for stock *i* on day *d.* According to H(1.1), if institutional investors are worse off in trading execution during extreme days, the value of β_1 for buy/ (sell) price ratio of institutional investors should be positive (negative). Everything else equal, difference in price ratio comparison among investor types means that one type of investor is at a disadvantage relative to another type of investor. After we compute price ratio difference and test whether it is significant, we then run the following regression model to investigate whether the price ratio difference can be explained by stock and trade-related characteristic.

$$Price\ ratio^{d}_{i,(re-ins)} = \beta_0 + \beta_1 dumExtreme^{d}_{i} + \beta_2 lsize^{d}_{i} + \beta_3\, pe^{d}_{i} + +\beta_4 avgturn^{d}_{i}$$
$$+\beta_5 avgvol^{d}_{i} + \varepsilon^{d}_{i}$$

Due to time constraint and advantages institutions possess over retails might become less effective in extreme market, the value of β_1 for buy/ (sell) price ratio difference should be negative (positive) according to H(1.2).

3.3.2 Aggressiveness level (H2)

We calculate aggressive trading measurement by following the methodology of Agarwal, Faircloth, Liu, and Rhee (2009) where two measurements can prevail the aggressiveness level of investors: (i) order initiation rates, and (ii) order execution rates.

$$Order\ initiation\ rates\ ^{d}_{i,j} = \frac{Number\ of\ initiation\ order^{d}_{i,j}}{Total\ number\ of\ executed\ order^{d}_{i,j}}$$

We compute order initiation rates of investor type *j* for stock *i* on day *d* as mentioned above which can be interpreted as the more aggressive investor group exhibits the higher order initiation rate. Then, order execution rates of investor type *j* for stock *i* on day *d* will further be calculated as these rates, which can be observed relatively higher for the more aggressive investor type.

$$Order\ execution\ rate\ ^{d}_{i,j} = \frac{Number\ of\ filled\ order^{d}_{i,j}}{Total\ number\ of\ submitted\ order^{d}_{i,j}}$$

To test order aggressiveness hypotheses (2.1 and 2.2), we regress fundamentally the same regression model as H1 but with different dependent variables. The dependent variables are order initiation rate and order execution rate which will be conducted regression separately for each investor type *j* for stock *i* on day *d*. Controlling the same set of variables from H1, we establish the regression models as follow:

$$OIR_{i,j}^{d} = \beta_0 + \beta_1 dumExtreme_i^d + \beta_2 lsize_i^d + \beta_3 pe_i^d + +\beta_4 avgturn_i^d$$
$$+\beta_5 avgvol_i^d + \varepsilon_i^d$$
$$OER_{i,j}^{d} = \beta_0 + \beta_1 dumExtreme_i^d + \beta_2 lsize_i^d + \beta_3 pe_i^d + +\beta_4 avgturn_i^d$$
$$+\beta_5 avgvol_i^d + \varepsilon_i^d$$

where OIR and OER denote order initiation rate and order execution rate respectively. To test H(2.1), the value of β_1 for institutional investors should be positive for both buy and sell orders. Similar methodology to H1, we apply T-statistic to test whether order initiation rate difference and order execution rate difference are statistically significant or not. It is expected that the rate difference should be significant for both buy and sell of order initiation and order execution because institutional investors are likely to react more aggressively to capture the profit from large price gap.

4. Empirical Results

In this section we will show two main sets of empirical tests to provide insights of which investor execute their trades at better or worse price during large price volatility movements. Our two main tests are (i) price ratio analysis to observe executed trade price performance, and (ii) order initiation and execution rate analysis to investigate trading behavior of investors during extreme days. We employ both T-statistic test and regression model in this study.

4.1 Price ratio

H(1.1)*: Institutional investors execute their trades at worse price during extreme market period than that of normal market period*

H(1.2)*: Institutional investors execute their trades at worse price than retail investors during extreme market period*

Our criteria for the *'extreme days'* are days when stock returns are at or higher than 99th percentile and at or lower than 1th percentile. *'Normal days'* are days when stock returns fall between 60th and 40th percentile. We then compute average price ratio for each investor groups. Addition to price ratios of each investor group, we also show the difference in price ratios, because they offer a measure how one group of investor performance relative to another group. During our sampling period, 1792 observations during extreme days and 15,327 observations during normal days are reported as shown in Table 1.

We exclude the remaining days in our test because they do not fall into either of our criteria for extreme and normal days. **Table 2** shows a summary statistics of price ratio in extreme days **(Panel A)** and normal days **(Panel B)**, including mean and standard deviation of price ratio, minimum price ratio, maximum price ratio and number of observations.

Table 2: Summary statistics of price ratio for each investor type and price ratio differences

This table shows the summary statistics for price ratio of retail and institution investors. Price ratios are defined as follow:

$$Price\ ratio\ _{i,j}^{d} \quad = \frac{volume\ weighted\ average\ price\ _{i,j}^{d}}{volume\ weighted\ average\ price\ _{i}^{d}} \times 100$$

$$Price\ ratio_{i,(re-ins)}^{d} = Price\ ratio_{i,retail}^{d} - \ Price\ ratio_{i,institution}^{d}$$

where *j* is investor type (retail/institution); *i* is constituent stock; *d* is trading day. *re* and *ins* denote retail investors and institutions investor respectively. *re-ins* denote price ratio difference of retail minus institution. Results of price ratio of investors are reported in groups according to the type of orders submitted: buy order and sell order. We present buy and sell price ratio of each investors group and price ratio difference between them during extreme days in Panel A and that of during normal days in Panel B. During our sample period, 2008-2017, number of observations, *N*, for extreme days and normal days are 1729 and 14808, respectively.

Panel A: Extreme days					
	Mean	**SD**	**Min**	**Max**	**N**
BUY					
Price ratio (re)	99.9157	0.4003	96.8671	102.0662	1729
Price ratio (ins)	100.0524	0.8293	94.0621	104.6169	1729
Price ratio difference (re-ins)	-0.1367	1.0302	-5.8029	6.1299	1729
SELL					
Price ratio (re)	100.0668	0.4266	97.8708	103.4982	1729
Price ratio (ins)	99.9595	0.7726	94.2159	105.9939	1729
Price ratio difference (re-ins)	0.1073	1.0035	-5.9943	5.3285	1729

Panel B: Normal days					
	Mean	**SD**	**Min**	**Max**	**N**
BUY					
Price ratio (re)	99.9272	0.1614	95.8092	100.9384	14808
Price ratio (ins)	100.0426	0.1811	97.5740	102.2333	14808
Price ratio difference (re-ins)	-0.1154	0.2711	-4.9841	2.5052	14808
SELL					
Price ratio (re)	100.0820	0.1572	98.8325	102.7644	14808
Price ratio (ins)	99.9555	0.1781	97.9853	103.3644	14808
Price ratio difference (re-ins)	0.1265	0.2701	-3.2325	4.4594	14808

4.1.1 T-statistic test for price ratio

Table 3 represents T-statistics results; in this test, we use two-tailed test for statistical significance testing. We categorize price ratio during extreme days in Panel A and during normal days in Panel B separately. As shown in **Panel A** which demonstrates the price ratios (multiply by 100) in extreme days, *buy* price ratios of retail and institution are 99.9190 and 100.0563 respectively. Significantly, this implies that retails bought 0.081% cheaper than average daily price paid while institutions paid 0.0563% more when buying stocks in extreme days. Price ratio difference of -0.1392 suggests that retail investors bought stocks at a price that is, on average, 0.1392% cheaper than price paid by institutional investors.

Next, we examine trading performance for selling stocks. In *sell session* of Panel A, price ratio of retail is 100.0668 and that of institution is 99.9600 which can be interpreted that retails sold at a price that is 0668% higher whereas institutions sold at price of 0.04% lower if compared with average selling price. As shown in Panel A, price ratio difference report similar results for buy and sell orders. In general, institution investors executed their trades at worse price than retail investors during extreme days.

Let us now explore each investor group performance during the normal days where there is no large price movement. As presented in *buy session* of **Panel B**, the price ratio for retail is 99.9272 and 100.0426 is for institution price ratio. On average, retail investors traded at better prices than average buying price by 0.0728%. However, institutions paid 0.0426% more than average price. In comparison, retail investors generally bought stocks at more favorable price than institution by 0.1154%. For *sell* orders, price ratio of retails and institutions are reported respectively as 100.0802 and 99.9555. With statistically significant, retail sold stocks at better price by 0.0802% whereas institutions received less favorable price by 0.0444% when compare to average selling price of the day. In aggregate, institutions executed their trades at less favorable price than retails in normal days.

After we examine price ratio of different investors in same market condition, we further investigate price ratios of same investor type but different market condition. In *buying* stocks, we find that retails purchased stocks cheaper than average selling price both in extreme and normal days. On the other hand, institutions purchased more expensive than average. When we compare same investor performance in two market conditions, retail bought at more favorable price but institutions bought slightly more expensive in extreme days than normal days. In *selling* stocks, retails sell price ratio became slightly less in extreme days and sell price ratio of institutions slightly improved in extreme days as compared to normal days.

Table 3: Price ratio and price ratio difference for each type of investors

This table shows the t-statistics result for price ratio of retail and institution investors. Price ratios are defined as follow:

$$Price\ ratio_{i,j}^{d} = \frac{volume\ weighted\ average\ price_{i,j}^{d}}{volume\ weighted\ average\ price_{i}^{d}} \times 100$$

$$Price\ ratio_{i,(re-ins)}^{d} = Price\ ratio_{i,retail}^{d} - Price\ ratio_{i,institution}^{d}$$

where *j* is investor type (retail/institution); *i* is constituent stock; *d* is trading day. *re* and *ins* denote retail investors and institutions investor respectively. *re-ins* denotes price ratio difference of retail minus institution. Results of price ratio are reported in groups according to the type of orders submitted: buy order and sell order. We present buy and sell price ratio of each investors group and price ratio difference between them during extreme days in Panel A and that of during normal days in Panel B separately. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

Panel A: Extreme days		
	Mean	**P-value**
BUY		
Price ratio (re)	99.9190	0.0000***
Price ratio (ins)	100.0563	0.0142**
Price ratio difference (re-ins)	-0.1392	0.0000***
SELL		
Price ratio (re)	100.0668	0.0000***
Price ratio (ins)	99.9600	0.0214**
Price ratio difference (re-ins)	0.1069	0.0000***
Panel B: Normal days		
	Mean	**P-value**

BUY		
Price ratio (re)	99.9290	0.0000***
Price ratio (ins)	100.0414	0.0000***
Price ratio difference (re-ins)	-0.1125	0.0000***
SELL		
Price ratio (re)	100.0802	0.0000***
Price ratio (ins)	99.9558	0.0000***
Price ratio difference (re-ins)	0.1243	0.0000***

In summary, we see slight improvement of institutional investor sell transaction while buy transaction performance is worse off. One significant finding is institutions appear to trade at less favorable price than average price in any event regardless of market conditions and order types. As we expected, institutions clearly trade at worse price than retail during large volatility days. Particularly, on average, institution investors executed trades at relatively worse price, by 0.1392% for buy orders and 0.1069% for seller orders, than retail investors. One plausible explanation can be that sophisticated investment tools which institutions possess over retails probably not make them gain trading advantages to improve order execution price during large volatility days. Another possible explanation is that the investment portfolio size for institutions are naturally larger than retails. Easley and O'hara (1987) states that, assuming institutional investors as informed traders, they are likely to place large order size to maximize the profit from short-lived information. Rather than sophisticated investment tools, fast execution become all the matters to take advantage from short-lived large price movements. Together with the needs to execute large trades fast, this exacerbate execution price of institutions' orders to be worse than retails.

4.1.2 Regression test for price ratio

In previous section, we observe that retail investors tend to outperform institutional investors when they executed stocks during extreme days. The price ratio mean value from T-statistics can shed some light in comparing trading performance between two groups of investors. Nevertheless, we do not know the impact towards performance of each investor from market conditions.

To understand the variation of investors trade execution performance across different market condition, we further perform the regression analysis where *price ratio* as *dependent variables* and *extreme days as dummy variables* to proxy for market conditions while controlling stock and trade-related characteristics. We follow the method from Choe et al. (2005) which is later utilized by Ekkayokkaya et al. (2020). This regression analysis also helps as robustness check for our price ratio tests, since the results we observed in previous section may be driven by these controlling factors rather than different market conditions. The regression model is as follow:

$$Price\ ratio_{i,j}^{d} = \beta_0 + \beta_1 dumExtreme_i^d + \beta_2 lsize_i^d + \beta_3\, pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d \quad \text{(equation 4)}$$

$$Price\ ratio_{i,re-ins}^{d} = \beta_0 + \beta_1 dumExtreme_i^d + \beta_2 lsize_i^d + \beta_3\, pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d \quad \text{(equation 5)}$$

The dependent variable, $Price\ ratio_{i,j}^{d}$, is buy and sell price ratio of each investor type *j* for stock *i* on day *d.*

Table 4 displays descriptive statistics of the independent variables used in the regression equation (4) and equation (5). During our 10-years sampling period, we observe that average Thai's stocks are traded at P/E, *pe,* 15.6844 and 18.8532 times during extreme days and normal market days respectively. Stock turnover, *avgturn*, shows number of stocks traded in a day. 0.6426% of total share outstanding on extreme days and 0.4158% on normal days indicates that investors tend to trade more stocks when large price movement occurs. They are likely to take the opportunity of capturing large price gap in extreme days. In terms of volatility, the swing from daily bottom to daily peak, *avgvol*, are 2.0045% during extreme days and 1.2445% on normal days. Meaning that the larger market price swing, the higher volatility of stocks.

Table 4: Summary statistics of independent variables used in regression

A. Extreme days					
Independent variables	**Mean**	**SD**	**Min**	**Max**	**N**
lsize	24.6504	1.3035	21.6663	27.6782	1729
pe	15.6844	13.3200	0.7378	84.8629	1729
avgturn	0.6426	0.8386	0.0162	5.9292	1729
avgvol	2.0045	0.8585	0.4933	5.7003	1729
B. Normal days					
Independent variables	**Mean**	**SD**	**Min**	**Max**	
lsize	25.2668	1.2399	21.5165	27.8596	14808
pe	18.8532	14.5332	0.9888	99.4596	14808
avgturn	0.4158	0.4882	0.0273	6.4457	14808
avgvol	1.2445	0.4689	0.4124	5.5053	14808

Table 5 represents the regression analysis of price ratio and different market condition. According to H(1.1), we expect to see the coefficient of dummy variables for institutions' price ratio to be positive for buy orders and negative for sell orders. Inversely, dummy variables show negative for buy price ratio and positive for sell price ratio. This means that extreme market conditions is associated with slightly improvement in price ratio of institutions. However, this observations being statistically insignificant, such improvement of institutional investors might not have association with extreme market condition. Besides, the incremental amount of price ratio is rather small.

Table 5: Regression estimates of price ratio of each investor type and different market conditions

This table shows the result from below regression equations;

$$Price\ ratio_{i,re}^{d} = \beta_0 + \beta_1 dumExtreme_i^d + \beta_2 lsize_i^d + \beta_3 pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d$$

$$Price\ ratio_{i,ins}^{d} = \beta_0 + \beta_1 dumExtreme_i^d + \beta_2 lsize_i^d + \beta_3 pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d$$

where buy and sell price ratio of retails and institutions regress with the following independent variables: *dumExtreme* is dummy variables equal to 1 if the market is during extreme day, 0 if the market during normal days, *lsize* is log of market capitalization on previous day; *pe* is price to earnings on previous day, *avgturn* is average of previous 20 daily stock turnover, and *avgvol* is average of previous 20 daily price volatility. *re* and *ins* denote retail investors and institutional investors, respectively. *re-ins* denotes price ratio difference of retail minus institution. Coefficients of each independent variables for price ratio of each investor types are reported as groups according to order type: buy order and sell order. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

	Regression coefficients			
Independent variables	**Buy price ratio**		**Sell price ratio**	
	(Retail)	(Institution)	(Retail)	(Institution)
Intercept	99.9349***	100.1165***	100.2317***	99.9086***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
dumExtreme	0.0028	-0.0057	-0.0324***	0.0156
	(0.6124)	(0.9883)	(0.0000)	(0.1619)
lsize	-0.0004	-0.0036*	-0.0067***	0.0026
	(0.7608)	(0.0859)	(0.0000)	(0.1963)
pe	0.0000	0.0000	-0.0001	-0.0002
	(0.7516)	(0.9842)	(0.6074)	(0.2929)
avgturn	0.0514***	-0.0230***	-0.0483***	0.0283***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
avgvol	-0.0322***	0.0222***	0.0317***	-0.0218***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. of observation	16537	16537	16537	16537
Adjusted R^2	0.0159	0.0018	0.0155	0.0022

To further investigate the association of price ratio difference and market condition, we report regression estimates in **Table 6**. The dummy variables for price ratio difference shows positive for buy and negative for sell which is not as our initial expectation. We originally expect to see a negative coefficient for buy orders and positive coefficient for sell orders (For buy transaction, the difference is calculated from *Retails minus Institution*, so we are expecting the gap to be even wider). However, only coefficient of extreme market dummy variable is statistically significant in sell orders. Therefore, what we see here is extreme market condition contribute a smaller difference of trading performance between institutional and retails investors for sell orders.

Table 6: Regression estimates of price ratio difference and different market condition

This table shows the result from below regression equations;

$$Price\ ratio^{d}_{i,re-ins} = \beta_0 + \beta_1 dumExtreme^{d}_{i} + \beta_2 lsize^{d}_{i} + \beta_3\, pe^{d}_{i} + +\beta_4 avgturn^{d}_{i} + \beta_5 avgvol^{d}_{i} + \varepsilon^{d}_{i}$$

where buy and sell price ratio difference (retail minus institution) regress with the following independent variables: *dumExtreme* is dummy variables equal to 1 if the market is during extreme day, 0 if the market during normal days, *lsize* is log of market capitalization on previous day; *pe* is price to earnings on previous day, *avgturn* is average of previous 20 daily stock turnover, and *avgvol* is average of previous 20 daily price volatility. *re* and *ins* denote retail investors and institutional investors, respectively. *re-ins* denotes price ratio difference of retail minus institution. Coefficients of each independent variables for price ratio differences are reported as groups according to order type. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

	Regression coefficients

Independent variables	Buy price ratio difference (Retail – Institutions)	Sell price ratio difference (Retail – Institutions)
Intercept	-0.1816**	0.3231***
	(0.0144)	(0.0000)
dumExtreme	0.0030	-0.0479***
	(0.7998)	(0.0000)
lsize	0.0041	-0.0093***
	(0.1489)	(0.0008)
pe	0.0000	0.0001
	(0.8914)	(0.6070)
avgturn	0.0744 ***	-0.0766***
	(0.0000)	(0.0000)
avgvol	-0.0544 ***	0.0535***
	(0.0000)	(0.0000)
No. of Observation	16537	16537
Adjusted R^2	0.0082	0.0093

4.2 Trade Aggressiveness

H(2.1): *Institutional investors are more aggressive in order submission during extreme market period than that of normal market period*

H(2.2): *Institutional investors are more aggressive in order submission than retail investors during extreme market period*

The findings in previous section indicate that the execution performance of institution investors relative to that of retail investors are still relatively worse during extreme days. Consequently, we look for the investors' behavior during extreme days in order to understand how they will be impacted. One aspect of trading behavior, we investigate 'trading aggressiveness' by looking at these two proxies: *(i) order initiation rates* and *(ii) order execution rates*. As stated in Agarwal, S., et al (2009), the more aggressive traders are more likely to initiate trades to improve the speed of execution. For order execution rates, the underlying presumption is that if one group of traders is more aggressive than the other, the execution rate of their orders should be higher.

In order to conduct our main test, **Table 7** and **Table 8** report the summary statistics of order initiation rate (OIR) and order execution rate (OER) for retail and institutions during extreme days and normal days. Order initiation rate (OIR) is calculated as the ratio of the number of orders initiated by an investor groups to the total number of executed orders submitted by the same investors group. For order execution rate (OER), the ratio is the number of executed orders from an investor group to the total number of orders submitted by the same investor groups.

Table 7: Summary statistics of order initiation rate (OIR)

This table shows summary statistics for order initiation rate of retail and institution investors. Order initiation rate is computed as follow:

$$Order\ initiation\ rates\,_{i,j}^{d} = \frac{Number\ of\ initiation\ order_{i,j}^{d}}{Total\ number\ of\ executed\ order_{i,j}^{d}} \times 100$$

where *j* is investor type (retail/institution); *i* is constituent stock; *d* is trading day. *re* and *ins* denote retail investors and institutions investor respectively. *re-ins* denotes order initiation rate difference of retail minus institution. Results of order initiation rate of investors are reported in groups according to the type of orders submitted: buy order and sell order. We present buy and sell order initiation rate of each investors group and rate difference between them during extreme days in Panel A and that of during normal days in Panel B. During our sample period, 2008-2017, number of observations, *N*, for extreme days and normal days are 1729 and 14808, respectively.

Panel A: Extreme days	**Mean**	**SD**	**Min**	**Max**	**N**
BUY					
Order initiation rate (re)	44.6368	4.2584	32.0504	58.5363	1729
Order initiation rate (ins)	57.3553	5.6399	37.4710	75.6285	1729
Order initiation rate difference (re-ins)	-12.7185	7.1531	-34.7083	11.1674	1729

SELL					
Order initiation rate (re)	56.6648	5.3763	39.5273	74.6185	1729
Order initiation rate (ins)	55.9177	4.2961	42.6188	71.4397	1729
Order initiation rate difference (re-ins)	0.7472	6.9574	-25.9123	23.4922	1729

Panel B: Normal days

	Mean	**SD**	**Min**	**Max**	**N**
BUY					
Order initiation rate (re)	43.0707	7.5311	15.3624	69.7882	14808
Order initiation rate (ins)	56.1272	8.2188	20.8740	87.1995	14808
Order initiation rate difference (re-ins)	-13.0565	11.0577	-55.7627	30.1096	14808
SELL					
Order initiation rate (re)	48.9224	8.0455	19.0970	77.8352	14808
Order initiation rate (ins)	55.2767	9.2710	18.7732	90.6446	14808
Order initiation rate difference (re-ins)	-6.3542	12.2489	-51.1666	40.1874	14808

Table 8: Summary statistics of order execution rate (OER)

This table shows the summary statistics for order execution rate of retail and institution investors. Order execution rate is computed as follow:

$$Order\ execution\ rate\ _{i,j}^{d} = \frac{Number\ of\ filled\ order_{i,j}^{d}}{Total\ number\ of\ submitted\ order_{i,j}^{d}} \times 100$$

where *j* is investor type (retail/institution); *i* is constituent stock; *d* is trading day. *re* and *ins* denote retail investors and institutions investor respectively. *re-ins* denotes order execution rate difference of retail minus institution. Results of order execution rate of investors are reported in groups according to the type of orders submitted: buy order and sell order. We present buy and sell order execution rate of each investors group and rate difference between them during extreme days in Panel A and that of during normal days in Panel B. During our sample period, 2008-2017, number of observations, *N*, for extreme days and normal days are 1729 and 14808, respectively.

Panel A: Extreme days

	Mean	**SD**	**Min**	**Max**	**N**
BUY					
Order execution rate (re)	45.8048	5.3813	27.3082	62.2642	1729
Order execution rate (ins)	61.2687	3.8536	48.0869	74.5238	1729
Order execution rate difference (re-ins)	-15.4639	6.5013	-36.4164	7.8920	1729
SELL					
Order execution rate (re)	47.3313	3.1521	36.1285	58.6022	1729
Order execution rate (ins)	59.1901	6.3044	41.3096	83.0275	1729
Order execution rate difference (re-ins)	-11.8588	7.0288	-33.6474	10.4215	1729

Panel B: Normal days					
	Mean	**SD**	**Min**	**Max**	**N**
BUY					
Order execution rate (re)	43.8210	4.5466	27.5862	61.1036	14808
Order execution rate (ins)	59.8332	3.8970	45.1613	74.7583	14808
Order execution rate difference (re-ins)	-16.0121	5.9489	-38.9650	8.8359	14808
SELL					
Order execution rate (re)	37.6655	3.2871	24.8731	49.5283	14808
Order execution rate (ins)	58.1242	6.2902	33.2131	82.8283	14808
Order execution rate difference (re-ins)	-20.4588	7.1022	-46.5130	10.3276	14808

4.2.1 T-statistic test for trade aggressiveness: OIR and OER

Order initiation rate (OIR)

Table 9 reports T-statistic result of OIR for each investor type and OIR difference between them. The interpretation is straight forward. The higher rate implies investors are more aggressive to initiate their trades. The OIR rates of each investor groups during extreme days and normal days are categorized separately in Panel A and Panel B of Table 8. In **Panel A** of *buy* session, retail investors generally initiate about 43.63% of their total executed orders while institutions initiate that of 57.36%. With significant evidence, institution investors are aggressive buyers than retails in extreme days. Similar interpretation is applied for *sell* orders as well. Out of total executed orders from retails, 56.66% are initiated orders on overage. And such percentage for institutions is 55.92%. Unlike buy orders, retails seems to be a bit more impatient relative to institutions for *sell* orders submission. In particular, their OIR is slightly higher than institutions' by 0.75%. It does not necessarily mean institutions became less aggressive in selling. In fact, OIR results show that institutions' aggressive trading behavior remains roughly similar for all order types. Therefore, we could see that dramatic increase in OIR for sell orders makes retails being impatient than institution. P**anel B** displays OIR of investors in normal days. To see variation in trading aggressiveness of one group in two market conditions, we compare OIR rates from Panel A and Panel B. Taken together, we found statistically strong evidence that institution investors become slightly more impatient to initiate their orders in extreme days compared to normal days which supports H (2.1). Regarding H (2.2), we found institutions' aggressiveness over retails only in buy orders. In sell orders, retails' OIR is higher than institution by very small amount.

Table 9: Order initiation rate (OIR) for each investor type and OIR difference between investor groups (T-statistics results)

This table shows the t-statistics result for order initiation rate of retail and institution investors. Order initiation rate is computed as follow:

$$Order\ initiation\ rates\,{}^{d}_{i,j} = \frac{Number\ of\ initiation\ order^{d}_{i,j}}{Total\ number\ of\ executed\ order^{d}_{i,j}} \times 100$$

where *j* is investor type (retail/institution); *i* is constituent stock; *d* is trading day. *re* and *ins* denote retail investors and institutions investor respectively. *re-ins* denotes order initiation rate difference of retail minus institution. Results of order initiation rates are reported in groups according to the type of orders submitted: buy order and sell order. We present buy and sell order initiation rate of each investors group and rate difference between them during extreme days in Panel A and that of during normal days in Panel B separately. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

Panel A: Extreme days		
	Mean	**P-value**
BUY		
Order initiation rate (re)	44.6368	0.0000***
Order initiation rate (ins)	57.3553	0.0000***
Order initiation rate difference (re-ins)	-12.7185	0.0000***
SELL		
Order initiation rate (re)	56.6648	0.0000***
Order initiation rate (ins)	55.9177	0.0000***

Order initiation rate difference (re-ins)	0.7472	0.0000***
Panel B: Normal days		
	Mean	**P-value**
BUY		
Order initiation rate (re)	43.0707	0.0000***
Order initiation rate (ins)	56.1272	0.0000***
Order initiation rate difference (re-ins)	-13.0565	0.0000***
SELL		
Order initiation rate (re)	48.9224	0.0000***
Order initiation rate (ins)	55.2767	0.0000***
Order initiation rate difference (re-ins)	-6.3542	0.0000***

Order execution rate (OER)

If institution investors are more aggressive in initiating trades than retails, we expect their orders are more likely to get executed. In **Table 10**, results reveal that buy and sell orders submitted by institutions are executed at higher rates in extreme days than in normal days. Since institutions are constantly being aggressive in trading, the magnitude of their OER difference between extreme and normal days is quite small. On average, the rates increase from 59.8% to 61.2% for buy orders and from 58.1% to 59.2% for sell orders. With strong evidence, this supports hypothesis (2.1). Such that higher rate in order executing is related to higher rate in initiating those orders. Consequently, such order initiators are assumed as more aggressive traders. For hypothesis (2.2), we have sufficient evidence to support that OER of institutions are significantly higher than that of retail in extreme days. In particular, the rate differences are 15.46% for buy orders and 11.86% for sell orders.

Table 10: Order execution rate (OER) for each investor type and OER difference between investor groups

This table shows the t-statistics results for order execution rate of retail and institution investors. Order execution rate is computed as follow:

$$Order\ execution\ rate\ _{i,j}^{d} = \frac{Number\ of\ filled\ order_{i,j}^{d}}{Total\ number\ of\ submitted\ order_{i,j}^{d}} \times 100$$

where *j* is investor type (retail/institution); *i* is constituent stock; *d* is trading day. *re* and *ins* denote retail investors and institutions investor respectively. *re-ins* denotes order execution rate difference of retail minus institution. Results of order execution rate of investors are reported in groups according to the type of orders submitted: buy order and sell order. We present buy and sell order execution rate of each investors group and rate difference between them during extreme days in Panel A and that of during normal days in Panel B separately. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

Panel A: Extreme days		
	Mean	**P-value**
BUY		
Order execution rate (re)	45.8048	0.0000***
Order execution rate (ins)	61.2687	0.0000***
Order execution rate difference (re-ins)	-15.4639	0.0000***
SELL		
Order execution rate (re)	47.3313	0.0000***
Order execution rate (ins)	59.1901	0.0000***
Order execution rate difference (re-ins)	-11.8588	0.0000***

Panel B: Normal days		
	Mean	**P-value**
BUY		
Order execution rate (re)	43.8210	0.0000***
Order execution rate (ins)	59.8332	0.0000***
Order execution rate difference (re-ins)	-16.0121	0.0000***
SELL		
Order execution rate (re)	37.6655	0.0000***
Order execution rate (ins)	58.1242	0.0000***
Order execution rate difference (re-ins)	-20.4588	0.0000***
	43.8210	

4.2.2 Regression analysis on order aggressiveness: OIR and OER

Order initiation rate (OIR)

Given the evidence that institution investors' aggressiveness over retail investor, we further investigate the relationship between their aggressive behavior and extreme market condition. **Table 11** demonstrates the regression estimates of order initiation and execution rates. We employ OIR and OER as dependent variables while extreme market days as dummy variable to proxy different market conditions.

The coefficients of dummy variables are reported as positive value and statistically significant across all OIR for both retails and institutions. It means retails and institutions aggressively initiate their orders. In other words, extreme market condition is associated with the behavior of investors being more aggressive than normal days. The same interpretation applies for both buy and sell orders because we find similar results of positive and significant dummy coefficients. Therefore, the findings from order initiation rates supports our H(2.1). Regarding H(2.2), we cannot tell which investors is better than the other by seeing the coefficient dummy variables of OIR difference regression. It only shows that extreme market conditions contribute to the smaller OIR rates gap between retails and institutional investors.

Table 11: Regression estimates between order initiation rates and different market conditions

This table shows the result from below regression equations;

$$OIR_{i,re}^{d} = \beta_0 + \beta_1 Extreme_i^d + \beta_2 lsize_i^d + \beta_3\, pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d$$
$$OIR_{i,ins}^{d} = \beta_0 + \beta_1 Extreme_i^d + \beta_2 lsize_i^d + \beta_3\, pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d$$
$$OIR_{i,re-ins}^{d} = \beta_0 + \beta_1 Extreme_i^d + \beta_2 lsize_i^d + \beta_3\, pe_i^d + +\beta_4 avgturn_i^d + \beta_5 avgvol_i^d + \varepsilon_i^d$$

where buy and sell order initiation rate, *OIR*, of retails and institutions regress with the following independent variables: *Extreme* is dummy variables equal to 1 if the market is during extreme day, 0 if the market during normal days, *lsize* is log of market capitalization on previous day; *pe* is price to earnings on previous day, *avgturn* is average of previous 20 daily stock turnover, and *avgvol* is average of previous 20 daily price volatility. *re* and *ins* denote retail investors and institutional investors, respectively. *re-ins* denote order initiation rate difference of retail minus institution. Coefficients of each independent variables for order initiation rate of each investor types and order initiation rate difference are reported as groups according to order type. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

Independ: variables	*Regression coefficients*					
	Buy OIR			**Sell OIR**		
	Retail(1)	Ins (2)	(1)-(2)	Retail(1)	Ins (2)	(1)-(2)
Intercept	43.1062***	54.6355***	-11.5293***	49.6610***	55.4037***	-5.7426**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0094)
Extreme	1.5627***	1.1244***	0.3183	7.8124***	0.8056**	7.0068***
	(0.0000)	(0.0000)	(0.2886)	(0.0000)	(0.0012)	(0.0000)
lsize	-0.0061	0.0544	-0.0605	-0.0217	0.0095	-0.0312
	(0.9054)	(0.3331)	(0.4226)	(0.6933)	(0.8789)	(0.7073)
pe	0.0047	0.0038	0.0009	-0.0024	-0.0048	0.0024
	(0.2308)	(0.3823)	(0.8725)	(0.5706)	(0.3174)	(0.7062)
avgturn	0.1211	-0.0714	0.1925	0.0861	0.2035	-0.1174
	(0.3088)	(0.5856)	(0.2732)	(0.5013)	(0.1621)	(0.5440)
avgvol	-0.0173	0.0602	-0.0775	-0.1458	-0.2905*	0.1448
	(0.8917)	(0.6670)	(0.6796)	(0.2865)	(0.0618)	(0.4838)
No. of obs	16537	16537	16537	16537	16537	16537
Adj R^2	0.0042	0.0020	0.0000	0.0841	0.0005	0.0325

Order Execution rate (OER)

Next, we run the same regression analysis on another aspect of trade aggressiveness to see whether the results reveal in the similar pattern. As shown in **Table 12**, we observe both investor types have higher initiation rate (OIR) in extreme days. Same expectation as OIR, we expect a positive coefficient of dummy variables in OER, and what we see here is a positive value both in buy/sell orders for retail and institutional investors. Since these results are significantly found to be the same for all orders submitted by both investor types, we can conclude that extreme market condition have association with higher execution rates of orders submitted by both investor groups. In accordance with the underlying presumption, the higher execution rate implies the more aggressiveness in trading. Therefore, this supports our hypothesis (2.1).

In summary for H(2.2), computed OER value and dummy variable coefficient from regressions suggest that institutional investors is more aggressive than retail investors in all order types as well as more aggressive in extreme days than normal days. One thing to note is that retail investor shows higher level of the aggressiveness incremental (as reported from regression) which mainly contributed from sell transaction. Computed OIR value and dummy coefficients from regression show similar pattern to OIR, except for sell orders in extreme days whereby retail investors have about 0.75% (56.66% - 55.92%) higher OIR than institutional investors. Even though the value is small but this mean we cannot conclude that institutional investor is more aggressive than retails investor during extreme market condition, at least for sell transactions. Having said that, we find that institutional investor is more aggressive than retails investor in general.

Table 12: Regression estimates between order execution rates and different market conditions

This table shows the result from below regression equations;

$$OER\,^{d}_{i,re} = \beta_0 + \beta_1 Extreme^d_i + \beta_2 lsize^d_i + \beta_3\, pe^d_i + +\beta_4 avgturn^d_i + \beta_5 avgvol^d_i + \varepsilon^d_i$$
$$OER^{d}_{i,ins} = \beta_0 + \beta_1 Extreme^d_i + \beta_2 lsize^d_i + \beta_3\, pe^d_i + +\beta_4 avgturn^d_i + \beta_5 avgvol^d_i + \varepsilon^d_i$$
$$OER^{d}_{i,re-ins} = \beta_0 + \beta_1 Extreme^d_i + \beta_2 lsize^d_i + \beta_3\, pe^d_i + +\beta_4 avgturn^d_i + \beta_5 avgvol^d_i + \varepsilon^d_i$$

where buy and sell order execution rate, *OER*, of retails and institutions regress with the following independent variables: *Extreme* is dummy variables equal to 1 if the market is during extreme day, 0 if the market during normal days, *lsize* is log of market capitalization on previous day; *pe* is price to earnings on previous day, *avgturn* is average of previous 20 daily stock turnover, and *avgvol* is average of previous 20 daily price volatility. *re* and *ins* denote retail investors and institutional investors, respectively. *re-ins* denote order execution rate difference of retail minus institution. Coefficients of each independent variables for order execution rate of each investor types and rate differences are reported as groups according to order type. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

	Regression coefficients

Independ: variables	Buy OER			Sell OER		
	Retail(1)	Ins(2)	(1)-(2)	Retail (1)	Ins (2)	(1)-(2)
Intercept	44.5857***	59.2628***	-14.6770***	36.9996***	57.4650***	-20.4654***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Extreme	2.0483***	1.4437***	0.6046***	9.6459***	1.0845***	8.5613***
	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)
lsize	-0.0249	0.0218	-0.0467	0.0281	0.0246	0.0035
	(0.4468)	(0.4269)	(0.2702)	(0.2228)	(0.5799)	(0.9434)
pe	0.0006	0.0008	-0.0002	-0.0039**	0.0024	-0.0063
	(0.8257)	(0.7127)	(0.9456)	(0.0285)	(0.4765)	(0.1009)
avgturn	-0.0165	0.0508	-0.0673	0.0330	0.0396	-0.0066
	(0.8291)	(0.4258)	(0.4949)	(0.5385)	(0.7014)	(0.9549)
avgvol	-0.1064	-0.0099	-0.0966	0.0163	-0.0142	0.0305
	(0.1913)	(0.8849)	(0.3593)	(0.7760)	(0.8975)	(0.8062)
No. of obs	16537	16537	16537	16537	16537	16537
Adjusted R^2	0.0165	0.0123	0.0006	0.4490	0.0024	0.1205

Worse trading performance of retail investor in extreme market condition

Why are we seeing quite large incremental in aggressiveness of retail investors just only for sell orders? We try to answer this question by looking further into this behavior by separating the extreme market condition into 1) *Extreme raising* market condition and 2) *Extreme falling* market condition. We find that retail investors' *Price Ratio* for sell orders is actually worse along with significant incremental in order aggressiveness level which mostly happen in extreme gain market condition as shown in **Table 13**.

Table 13: Price ratio and price ratio difference for each type of investors in extreme days

This table shows the t-statistics result for price ratio of retail and institution investors. Price ratios are defined as follow:

$$Price\ ratio_{i,j}^{d} = \frac{volume\ weighted\ average\ price_{i,j}^{d}}{volume\ weighted\ average\ price_{i}^{d}} \times 100$$

$$Price\ ratio_{i,(re-ins)}^{d} = Price\ ratio_{i,retail}^{d} - Price\ ratio_{i,institution}^{d}$$

where *j* is investor type (retail/institution); *i* is constituent stock; *d* is trading day. *re* and *ins* denote retail investors and institutions investor respectively. *re-ins* denotes price ratio difference of retail minus institution. Results of price ratio are reported in groups according to the type of orders submitted: buy order and sell order. We present buy and sell price ratio of each investors group and price ratio difference between them during extreme raising days in Panel A and that of during extreme falling days in Panel B separately. In parentheses is p-value for statistical significance ***Significant at the 0.001 level, **Significant at the 0.05 level, and *Significant at the 0.1 level respectively.

Panel A: Extreme raising days	**Mean**	**P-value**
BUY		
Price ratio (re)	99.8776	0.0000***
Price ratio (ins)	99.9960	0.8806
Price ratio difference (re-ins)	-0.1184	0.0008***
SELL		
Price ratio (re)	100.0490	0.0000***
Price ratio (ins)	99.8741	0.0000***
Price ratio difference (re-ins)	0.1749	0.0000***

Panel B: Extreme falling days	**Mean**	**P-value**
BUY		
Price ratio (re)	99.9545	0.0000***
Price ratio (ins)	100.1054	0.0003***
Price ratio difference (re-ins)	-0.1509	0.0000***
SELL		
Price ratio (re)	100.0864	0.0000***
Price ratio (ins)	100.0354	0.1233
Price ratio difference (re-ins)	0.0510	0.1291

This behavior we see here might relate with the “disposition effect” in behavioral finance that explains the tendency of investors selling assets that have increased in value, while keeping assets that have dropped in value. In our case, retail investors would like to capture a gain when market is going up. During such large price movements, they might afraid that this opportunity may not last so they tend to use more aggressive orders and ended up facing price impact from using such orders. On the other hand, during market is going down, retail investors tend to keep those stocks with themselves or try to sell them at the best price they could (thus using less aggressive orders) as the pain from facing a loss is larger than the joy from making a gain. This disposition effect is one of the most fact that has been used to describe retail investor trading behavior. Nevertheless, this need to be further study before any conclusion can be drawn.

5. CONCLUSION

Our study, related to trade execution performance and order aggressiveness with intraday data from Stock Exchange of Thailand, shows that institutional investors trade at worse price when compare to retail investors not only during extreme market condition in which investors need to make a swift decision to execute their trades in order to capture a financial benefits from the market. Even though T-statistic numbers show an impact from trading execution during extreme market condition, (however, apart from price ratio of retail investors' sell transactions in extreme days where we see worse execution performance than normal days,) we cannot conclude that impacts we see in other transaction types are contributed from extreme market condition.

From aggressiveness standpoint, institutions, in general, are more aggressive in order submission than retails. In order executional rate (OER) section, we find that institutional investors always have their orders executed at higher rate regardless of market condition or order type. The same could be concluded for order initiation rate (OIR), for those orders that get executed, we find that institutional investors have higher rate of OIR except for sell orders in extreme days where retail investors become slightly more aggressive than institutional investors. OER and OIR data help explain the inconclusive on price ratio of other transactions (apart from retail sell transactions), even though both investors are more aggressive, as we see only a small incremental in OER and OIR for both investor types which means price impact from using market orders could be minimal. We believe our findings might relate to "disposition effect" in behavioral finance which help explain why we are seeing more aggressive orders from retail sell transactions (hence, worse trade execution performance) and this could be a promising room for further research.

REFERENCES:

Agarwal, S., Faircloth, S., Liu, C., & Rhee, S. G. (2009). Why do foreign investors underperform domestic investors in trading activities? Evidence from Indonesia. *Journal of Financial markets, 12*(1), 32-53.

Ahn, H. J., Bae, K. H., & Chan, K. (2001). Limit orders, depth, and volatility: Evidence from the stock exchange of Hong Kong. *The Journal of finance, 56*(2), 767-788.

Aitken, M., Brown, P., & Wee, M. (2007). Institutional versus retail traders: a comparison of their order placement strategies. In *University of Western Australia Working paper*.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies, 21*(2), 785-818.

Barclay, M. J., & Warner, J. B. (1993). Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics, 34*(3), 281-305.

Bessembinder, H., & Kaufman, H. M. (1997). A comparison of trade execution costs for NYSE and NASDAQ-listed stocks. *Journal of Financial and Quantitative Analysis*, 287-310.

Bloomfield, R., O'hara, M., & Saar, G. (2005). The "make or take" decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics*, *75*(1), 165-199.

Bushee, B. J. (2001). Do institutional investors prefer near-term earnings over long-run value? *Contemporary Accounting Research, 18*(2), 207-246.

Cao, C., Hansch, O., & Wang, X. (2008). Order placement strategies in a pure limit order book market. *Journal of Financial Research, 31*(2), 113-140.

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance, 24*(10), 1651-1679.

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance, 34*(8), 1911-1921.

Choe, H., Kho, B.-C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics, 54*(2), 227-264.

Choe, H., Kho, B.-C., & Stulz, R. M. (2005). Do domestic investors have an edge? The trading experience of foreign investors in Korea. *The review of financial studies, 18*(3), 795-829.

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal*, *51*(4), 31-37.

Demirer, R., & Kutan, A. M. (2006). Does herding behavior exist in Chinese stock markets? *Journal of international Financial markets, institutions and money, 16*(2), 123-142.

Dennis, P. J., & Strickland, D. (2002). Who blinks in volatile markets, individuals or institutions? *The Journal of finance, 57*(5), 1923-1949.

Easley, D., & O'hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, *19*(1), 69-90.

Ekkayokkaya, M., Jirajaroenying, S., & Wolff, C. C. (2020). Executing trades in style: retail investors vs. institutions. *Asia-Pacific Journal of Accounting & Economics*, 1-19.

Fong, K. Y., Gallagher, D. R., & Lee, A. D. (2014). Individual investors and broker types. *Journal of Financial and Quantitative Analysis*, 431-451.

Foucault, T. (1999). Order flow composition and trading costs in a dynamic limit order market. *Journal of Financial markets, 2*(2), 99-134.

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the street: Informational inefficiencies in a market with short-term speculation. *The Journal of finance, 47*(4), 1461-1484.

Glosten, L. R. (1994). Is the electronic open limit order book inevitable? *The Journal of finance, 49*(4), 1127-1161.

Harris, L., & Hasbrouck, J. (1996). Market vs. limit orders: The SuperDOT evidence on order submission strategy. *Journal of Financial and Quantitative Analysis*, 213-231.

Hasbrouck, J., & Saar, G. (2002). *Limit orders and volatility in a hybrid market: The Island ECN. Stern School of Business Dept*. Retrieved from

Hoffmann, A. O., Post, T., & Pennings, J. M. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance, 37*(1), 60-74.

Jones, C. M., & Lipson, M. L. (1999). Execution costs of institutional equity orders. *Journal of Financial Intermediation, 8*(3), 123-140.

Keim, D. B., & Madhavan, A. (1997). Transactions costs and investment style: an inter-exchange analysis of institutional equity trades. *Journal of Financial Economics, 46*(3), 265-292.

Kelley, E. K., & Tetlock, P. C. (2013). How wise are crowds? Insights from retail orders and stock returns. *The Journal of finance, 68*(3), 1229-1265.

Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian economics, 22*(6), 495-506.

Li, W., & Wang, S. S. (2010). Daily institutional trades and stock price volatility in a retail investor dominated emerging market. *Journal of Financial markets, 13*(4), 448-474.

Rock, K. (1996). The specialist's order book and price anomalies. *Review of Financial Studies, 9*, 1-20.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American economic review*, 465-479.

Seppi, D. J. (1997). Liquidity provision with limit orders and a strategic specialist. *The review of financial studies, 10*(1), 103-150.

Thaler, R. H., & Shefrin, H. M. (1981). An economic theory of self-control. *Journal of political economy, 89*(2), 392-406.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty, 5*(4), 297-323.

Wald, J. K., & Horrigan, H. T. (2005). Optimal limit order choice. *The Journal of Business, 78*(2), 597-620.

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