Volume Components and Return Predictability in Abnormal Trading Events

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จุฬาลงกรณ์มหาวิทยาลัย
CHULALONGKORN UNIVERSITY

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การพยากรณ์ผลตอบแทนด้วยส่วนประกอบของปริมาณการซื้อขายในสภาวะที่มีปริมาณการซื้อขายผิดปกติ

นายเจตริน เจริญพรพจน์

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วิทยานิพนธ์ฉบับนี้ศึกษาของความสามารถในการพยากรณ์ผลตอบแทนของปริมาณการซื้อขายประเภท 3 ประเภท ได้แก่ ปริมาณการซื้อขายรวม ปริมาณการซื้อ และ ปริมาณการขายในตลาดหลักทรัพย์แห่งประเทศไทยระหว่างปี 2555 ถึง 2561 เพื่อที่จะวัดความสามารถในการพยากรณ์ ข้าพเจ้าได้ทำการจัดกลุ่มหุ้นโดยแบ่งตามความผิดปกติในการซื้อขายและประเภทของปริมาณการซื้อขาย ข้าพเจ้าได้ทดสอบและยืนยันสมมุติฐานว่าปริมาณการซื้อ และ ปริมาณการขายขายที่ผิดปกตินั้นสามารถพยากรณ์ผลตอบแทนได้ โดยปริมาณการซื้อที่สูงผิดปกตินั้นสามารถพยากรณีได้ว่าในวันถัดไปหลักทรัพย์นั้นจะให้ผลตอบแทนที่เป็นบวก ในขณะที่ปริมาณการขายขายที่ผิดปกตินั้นสามารถพยากรณ์ได้ว่าในวันถัดไปหลักทรัพย์นั้นจะให้ผลตอบแทนที่เป็นลบ นอกเหนือจากนั้นข้าพเจ้ายังได้ทำการทบสอบและพบว่าผลตอบแทนที่เป็นบวกจากปริมาณการซื้อที่มากผิดปกตินั้นมีส่วนที่เป็นผลจากการบอกใบ้ถึงข่าวดีในวันถัดไป อย่างไรก็ตามข้าพเจ้าไม่พบว่าปริมาณการซื้อขายที่มากผิดสามารถดึงดูดความสนใจของนักลงทุนได้

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This paper examines return predictability of three types of trading volumes include total volumes, buy volumes and sell volumes in Thailand's stock market between 2012 to 2018. To measure predictability ability, we sort securities into group base on the level of trading volumes and type of volumes. We test and confirm that buy volumes and sell volumes can predict return one day after the abnormal trading event. Abnormal high buy volumes can predict positive next day return of that security while abnormal high sell volumes can predict negative next day return. In addition, we test and found that positive return from abnormally high buy volumes is the result of good news signaling. However, we cannot find significant evidence that abnormal high trading volumes from each type can catch investor attention.

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CHAPTER 1

INTRODUCTION

1.1 Background and Significance of the Problem

Volumes are widely used as a measurement of trading activity. It is the number of exchanges that occurs when market agents assign different values to an asset (Karpoff 1986). In an efficient market hypothesis, volumes should not have any power to predict return over an appropriate measure of risk. However, many literatures that study relationship between trading volume and price movement have found results, which are inconsistent with the efficient market hypothesis. Early study found that trading volume has a positive correlation with price change (Karpoff 1986). More recent study by Gervais, Kaniel et al. (2001) find that abnormal trading volume can predict future return (High volume return premium) and he interprets this as a result of investor recognition hypothesis originated by (Miller 1977). Zhong, Chai et al. (2018), by using a different way to measure abnormal volume, discovered high volume return premium in Australian market. However, some researchers argue that not every market has high volume return premium (e.g., Kaniel, Ozoguz et al. (2012); Huang, Heian et al. (2011). Wang, Wen et al. (2017) find the opposite effect called high volume return discount in China stock market and interpret it as a result of speculative environment.

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However, in a given trading period, volumes consist of buy volumes, sell volumes and ATO/ATC volumes. Buy volumes are the result of stockholder placing limit orders at ask while stock buyer placing market orders or marketable limit orders. Sell volumes are the result of stock buyer placing limit orders at bid while stockholder placing market orders or marketable limit orders. ATO (ATC) volumes are originated from auction system from both sides at the time market open (close). When traders want to execute trading, they can choose between limit orders, marketable limit orders and market orders. Limit orders characteristic is to provide liquidity to the market while market orders and marketable limit orders characteristics are to consume liquidity from the market. Compare to market orders and marketable limit orders, limit orders have higher adverse selection risk due to the arrival of new information and a higher risk that the order will not be executed. However, these drawbacks are traded off with the possibility to get the stock at more favorable price (Bae, Jang et al. (2003)). According to these characteristics, abnormally increasing in buy or sell volume should indicate arrival of new information.

1.2 Contribution

Instead of using total volumes to measure abnormal activities as in the previous researches, this study will investigate the result created by abnormal buy volume and abnormal sell volumes event. First, we expect that the resulting predictabilities corresponding to different types of the volumes to be different. Based on past literatures, a high-volume event can catch investor attention. Therefore, we hypothesize that each type of volume can catch attention of investor but the power to grab the attention may differ among them. Another reason that may explain the different outcome between each type of volume is the adverse selection between order initiator (market and marketable limit order) and liquidity provider (limit order). We hypothesize that people with new information in hand should take an action using market or marketable limit orders in the same direction with new information if they can. We expect that the categorization of volume can bring an important aspect to our study.

1.3 Objective

This paper's main objective is to examine whether disaggregation of total volume into buy and sell volumes can predict return in abnormal trading event. Furthermore, we will investigate whether each type of volume predict different return in abnormal trading event or not. Then, we will investigate whether the investor recognition hypothesis and the signaling hypothesis are the reasons behind predictability power and the difference in predictability.

1.4 Research Hypothesis

1.4.1 Main Hypothesis: Examination of Predictability Power

Hypothesis 1: Each kind of trading volume should have an ability to predict future stock return.

Our main objective is to test whether each kind of trading volume (Total volume, Buy volume and Sell volume) has any power to predict the future stock return in the Thai stock market. The efficient market hypothesis predicts that past price direction and volume should not have any predictive power over an appropriate measure of risk. However, many literatures that study the relationship between trading volume and price movement, even in the developed market, have found results, which are inconsistent with the efficient market hypothesis. This is why we expected that each kind of trading volume should have an ability to predict future stock return.

Hypothesis 2: We should observe a different degree of predictability power between each type of volume.

According to Chordia, Roll et al. (2002), total volume alone is absolutely guaranteed to conceal some important aspects of trading. The first possibility is they should give a different perspective to the new investor, which lead to differences in power to grab attention. Another possibility is information-signaling, disaggregation of total volume into buy and sell volumes should signal the directional of future information.

1.4.2 Possible Reason Behind Predictability

Hypothesis 3: If a type of volume can catch attention, after abnormal volume event, we should observe stocks without short sell have higher return compare to stocks with short sell when we use that type of volume to measure abnormal trading activity.

Merton (1987) indicates that if a stock is more publicly recognized, it will have more shareholder base. According to Miller (1977), an event that increases the number of people paying attention to a stock will increase the number of potential buyers while leaving the number of potential sellers largely unchanged (due to short sell constrain) which lead to an increase in price level. The fact that stocks which available for short-selling is easier for traders to take a negative position lead to the hypothesis that net buying flow (buy – sell) from new investor will be less on these stocks. This conclusion is based on assumption that new investors are mixing between buyers and sellers, which we expect that it should be the same for abnormal buy and abnormal sell volumes but with different proportion of buyers and sellers. Many literatures that study about abnormal volume event have used this visibility hypothesis to explain why abnormal volume event can predict future return (e.g., Gervais, Kaniel et al. (2001); Zhong, Chai et al. (2018)).

Hypothesis 4: After the abnormal high-volume event, we should observe the return gap between stocks without short sell and stock with short sell differ among each type of volume.

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We expect that the power of attention-grabbing to be diverse among types of volume due to each type of volume may convey different perspective to new investors (some may make new investor mostly buy while some may make new investor mostly sell after seeing the abnormal volume event). For example, if most of the people in the market have herding (contrarian) behavior, abnormal buy volumes should mostly grab the attention of buyers (sellers) while abnormal sell volumes should mostly grab the attention of sellers (buyers).

Hypothesis 5.1: We should observe abnormal increase in buy volumes before positive earnings surprise.

Hypothesis 5.2: We should observe abnormal increase in sell volumes before negative earnings surprise.

Each type of volume may signal the future direction of information content due to their different order initiator. Recall that buy volumes are the result of stockholder placing limit orders at ask and stock buyer placing market orders or marketable limit orders while sell volumes are the result of stock buyer limit orders at bid and stockholder place market orders or marketable limit orders. One of the possible events that make buy volumes and sell volumes increase abnormally is the arrival of good information and bad information respectively. If the market is in weak form efficiency, this mechanism should give a positive (negative) future return after abnormal high buy (sell) volumes event due to slow information digest and also may be the result of good (bad) news from the insider. If the market is in semi-strong form efficiency, this mechanism may indicate good (bad) news from the insider. No matter the market is weak or semi-strong form, this mechanism should give positive effect to future result.

CHAPTER 2

LITERATURE REVIEW

2.1 Concept and Theory

In the past, many researchers have studied about trading volumes. With the assumption that market agents frequently revise their demand prices and randomly encounter potential trading partners, Karpoff (1986) find that investor disagreement leads to increased trading but the observation of abnormal trading volumes does not necessarily imply disagreement and volumes can increase even if investors interpret the information identically if they also have had different past expectations. Moreover, he also finds that trading volumes have a positive correlation with a price change. A recent study by Gervais, Kaniel et al. (2001) finds that abnormal trading volumes can predict future positive return (High volume return premium) and they interpret it as a result of the attention-grabbing event. While Wang, Wen et al. (2017) find the opposite effect call high volume return discount in China stock market and they interpret it as a result of speculative environment.

To understand the mechanism of the attention-grabbing event. Following literatures are needed to acknowledge. Miller (1977) hypothesize that if volumes has an effect on attention, some of investors are likely to persuade themselves that the stock should be bough. Miller (1977) and Merton (1987) also predict that an increase in attention will tend to follow by price increasing. Gervais, Kaniel et al. (2001) found that past loser which considers as low visibility stock tend to get more effect of attention-grabbing event more compare past winner which consider as high visibility stock.

Unlike the past researches, our study use buy and sell volumes to measure the abnormal trading event instead of using total volumes. Buy volumes are the result of stockholder placing limit orders at ask and stock buyer place market orders or marketable limit orders while sell volumes are the result of stock buyer limit orders at bid and stockholder place market orders or marketable limit orders. Compare to market orders, limit orders has higher adverse selection risk due to the arrival of new information and a higher risk that the order will not be executed but they are traded off with a more favorable price (Bae, Jang et al. (2003)). With the assumption that investors who get new information will act on that information immediately. Abnormal high buy (sell) volumes of a stock should indicate the direction of the information. Moreover, if the market is in weak form efficiency, we should observe that future return of that stock is in the same direction as the information.

2.2 Empirical Finding of Predictability of Volumes

Many researchers have found that abnormal high trading volumes can predict a future positive return in US stock market (e.g., Gervais, Kaniel et al. (2001); Huang, Heian et al. (2011); Kaniel, Ozoguz et al. (2012)). However, results from outside US market are mixed. Kaniel, Ozoguz et al. (2012), find that developed market has stronger and consistent high volume return premium compare to emerging market. Huang, Heian et al. (2011), find no evidence of high-volume return premium in six Asian markets, including Japan and interpret it as a result of the difference in structural between US and Asian market. While recent research by Wang, Wen et al. (2017) find the oppose effect of high volume return premium called high volume return discount in China stock market and interpret it as a result of speculative environment. Apart from the relation between volumes and return, Akbas (2016) also finds that stocks with unusually low trading volume over the week prior to earnings announcements have more unfavorable earnings surprises. The literature is in line with W.Diamond and E.Verrecchia (1987) theory that under short-selling constraints, informed agents cannot trade on their negative information. While many researches focus on volume, some of the studies in the past suggest that different in buy-sell fraction inside volume should have a different implication. Chordia, Roll et al. (2002) argue that total volume alone is absolutely guaranteed to conceal some important aspects of trading and they also find that volume imbalance has the power to predict return.

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CHAPTER 3

DATA

All of our samples use data on the Stock Exchange of Thailand. Return, price and three type of volumes (Total, Buy and Sell Volumes) data between 2012 and 2018 are provided by E-finance program. For every type of volume that we study, following Gervais, Kaniel et al. (2001), first, we construct the daily sample by splitting the time interval between January 4, 2012, and May 17, 2018, into 30 nonintersecting trading intervals of 50 trading days. We skip a day between each trading interval for reasons that we want every day of week being used as formation date. Next, define the first 49 days as a reference period and the last day of the interval as formation date. Then, at the end of day 50, if volumes in the formation date are in last (first) decile of the trading interval we will define it as the high (low) volume stock. Otherwise, we will classify it as the normal volume. The graphic of time sequence is shown in Figure 1. Noted that in each trading interval, a stock will be excluded if it experiences data missing during that trading interval or price fall below one baht at formation period. The reason that we eliminate "Satang stock" is because stocks that have priced below one baht have spread bigger than one percent which might cause our result bias toward these Satang stock. Finally, at each formation date, we then get three groups of stock (High, Normal and Low) per type of volume. However, if we intersect buy volumes and sell volumes classification together, we then get nine groups of stock (shown in Figure 2.) which we will also use to for robustness check.

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For earnings surprise and earnings announcement date of all stock in Stock Exchange of Thailand between 2012 and 2018, provided by Bloomberg data providing, these data are used to investigate the relation between abnormal buy/sell volume that occur before earnings announcement and earnings surprise direction (hypothesis 5.1 and 5.2).

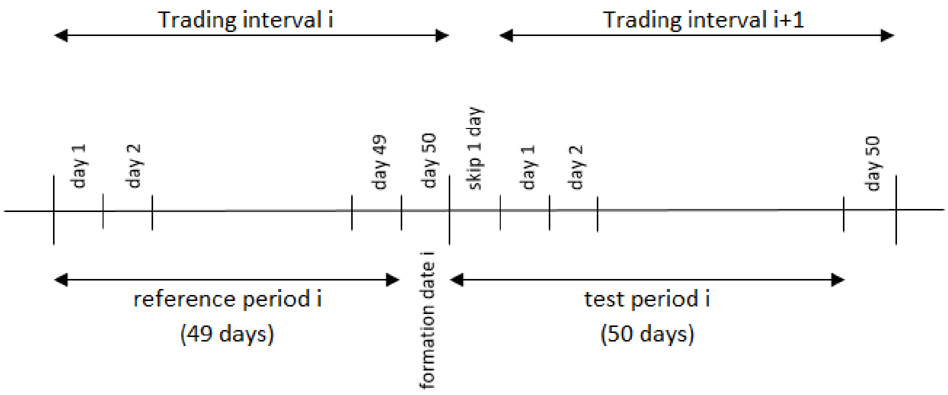

Figure 1. Time sequence for the daily sample.

Finally, the data set includes short sell volumes of stock in SET100 between 2012 and 2018 are provided by Thomson Reuters' data providing. We use these data to categorized stock with and without short sell, which we will use to investigate attention-grabbing hypothesis (hypothesis 3 and 4). The summary of data is shown in Figure 3.

	Low	Normal	High
Total Volume	LT	NT	HT
Buy Volume	LB	NB	HB
Sell Volume	LS	NS	HS

HSNHB(High buy not high sell)

LBNLS(Low buy not low sell)

		Buy		
		Low	Normal	High
Sell	High	LBHS	NBHS	HBHS
	Normal	LBNS	NBNS	HBNS
	Low	LBLS	NBLS	HBLS

HBNHS(High buy not high sell)

LSNLB(Low sell not low buy)

Figure 2. Group classification at formation date using both buy and sell volume.

Notation	Description	Unit	Source
Price	Daily price of stock	Bath	E-finance thailand
$R_{i,t}$	Daily return of stock i at formation date t	% / day	E-finance thailand
$VO_{i,t}$	Daily volumes of stock i at formation date t	Shares	E-finance thailand
$BUYVO_{i,t}$	Daily buy volumes of stock i at formation date t	Shares	E-finance thailand
$SELLVO_{i,t}$	Daily sell volumes of stock i at formation date t	Shares	E-finance thailand
$SUEAF_{i,t}$	Standardize unexpected earnings using analyst forecasts of stock i at quarter q of year t.	%	Bloomberg
Earning and Dividend announcement date	Average of stock i earning per share forecast by analyst within 90 day prior announcement date at quarter q of year t.	Date	Bloomberg
Short sell volume	Short sell volume	Shares	Thomson Reuters

Figure 3. Summary of the data.

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CHAPTER 4

METHODOLOGY

4.1 Portfolio Formation for Main Hypothesis

Following Gervais, Kaniel et al. (2001), at the formation date, we form portfolios using two methods. The first method is *Zero Investment Portfolio*. For every type of volume (Total, Buy and Sell), at every formation period, we take a long position in every high-volume stocks in that interval for one baht in total amount while taking a short position in every low volume stocks in that interval for one baht in total amount. Each stock in long and short portfolios is given equal weight. For example, if there are five stocks in the long portfolio, we will use 0.2 baht to buy each stock into the long portfolio. After that, I will observe the net return (NR) of this strategy for next 1/3/5/10/20/50 day after forming portfolio in every trading interval. By given each interval the same weight, average net return of this strategy is $\overline{NR} \equiv \frac{1}{30}\sum_{i=1}^{30} NR_i$. Noted that for this method, we will exclude any interval that has only high-volume shock or only low volume shock due to this method needed both long and short position to create a portfolio.

Contrast to the Zero Investment Portfolio method, this method called *Reference Return Portfolio* adjusts the weight given to each interval according to the number of securities that experience high or low volumes in the interval. However, in each portfolio, we still give equal weight on each security that comes from the same interval and from the same type of portfolio (Long/Short). We denote the test period return of any long (short) position net of the reference portfolio by $R_{ij}^{h}(R_{ij}^{l})$, where subscript i indicates the trading interval, the subscript j = 1,…., M_i^h(j $= 1, \ldots, M_i^l$) indicates the high-(low-) volume stocks for that interval, and NR represents net return. We will get

$$\bar{R}^h \equiv \frac{\sum_{i=1}^{30}\sum_{j=1}^{M_i^h} R_{ij}^h}{\sum_{i=1}^{46} M_i^h} \tag{1}$$

$$\bar{R}^l \equiv \frac{\sum_{i=1}^{30}\sum_{j=1}^{M_i^l} R_{ij}^l}{\sum_{i=1}^{244} M_i^l} \tag{2}$$

$$\overline{NR} \equiv \frac{\sum_{i=1}^{30}(\sum_{j=1}^{M_i^h} R_{ij}^h + \sum_{j=1}^{M_i^l} R_{ij}^l)}{\sum_{i=1}^{30}(M_i^h + M_i^l)} \tag{3}$$

To sum up, the different between two method is Zero portfolio is given equal weight to each formation date while reference portfolio is giving each stock an equal weight across time.

For both method and every type of volume, we use t-test to test hypothesis 1 whether net return of our strategy is significantly not equal to zero after control for our control variable. In addition, we use t-test to test hypothesis 2 whether net return of our strategy from a type of volume is significantly different from net return using other types of volume. Finally, to eliminate the chance that our result is biased by the formation date we pick. We then conduct the entire test again for fifty times. However, every time we start the new test, we shift the starting date one day toward the future to proof that our results are not a product of selection bias. Summary of our intervals created and how we use them are provided in Figure 4 and Figure 5 respectively.

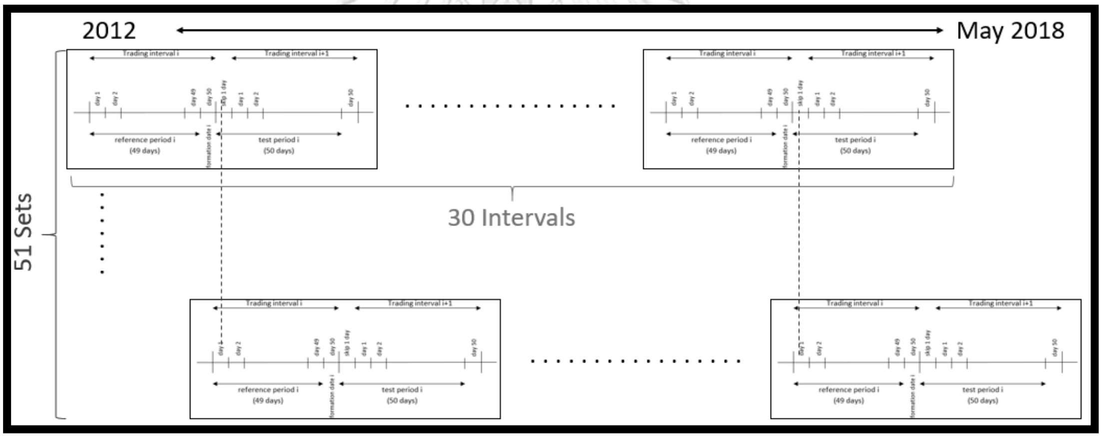

Figure 4. Summary of the data.

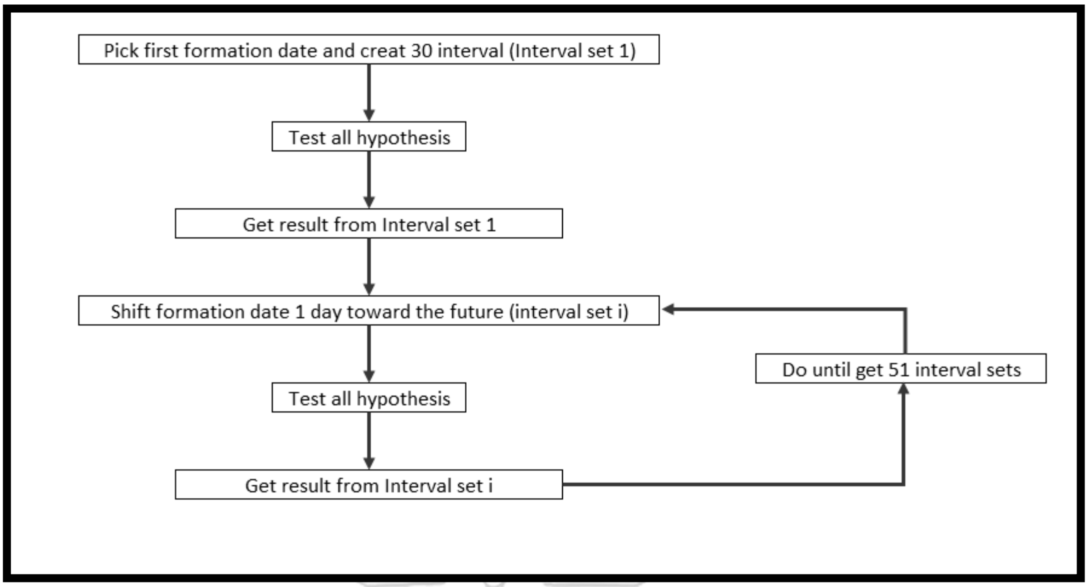

Figure 5. Summary of our intervals created.

4.2 Possible Reason Behind Predictability

For hypothesis 3, as noted in section 1.3.2, stocks which available for short-selling are easier for traders to take a negative position. For stocks that not available for short-selling, this fact indicates that new investors who their attention are caught by abnormal high-volume event have only option to buy lead to the higher return for this group. In order to verify this hypothesis, for every type of volume, first, we categorized stocks into two categories: stocks that available for short-sell in that interval and stocks that did not. Next, we apply the reference return strategy separate on these two subsamples. Then, we use t-test to test that the return of stocks without short-selling portfolio is significantly higher than stocks with short-selling stocks portfolio.

If hypothesis 3 is proved to be true. To prove that different types of volume have a different power to catch attention (Hypothesis4). We will use t-test to test that the gap between short-selling stocks and ordinary stocks is significantly different when we use different type of volume to classify the abnormal trading event.

To test hypothesis 5.1 and 5.2 that abnormal volume event is classified as signaling event. First, following Gervais, Kaniel et al. (2001), we investigate buy volume and sell volume one day before announce event. Given day 0 is the announcement date. We measure unusual buy and sell volumes by comparing daily stock's buy and sell volume of event period (one day before announce event) with reference period (trading day -50 to trading day -2). The graphic of time sequence is shown in Figure 6. Next, a stock is classified as high buy (sell) volume stock if its buy (sell) volumes in event period are in the top 10% of its reference period. And a stock is classified as low buy (sell) volume stock if its buy (sell) volumes in event period are in the bottom 10% of its reference period. Then, we use t-test to test whether abnormal high buy (sell) volume can predict positive (negative) news or not.

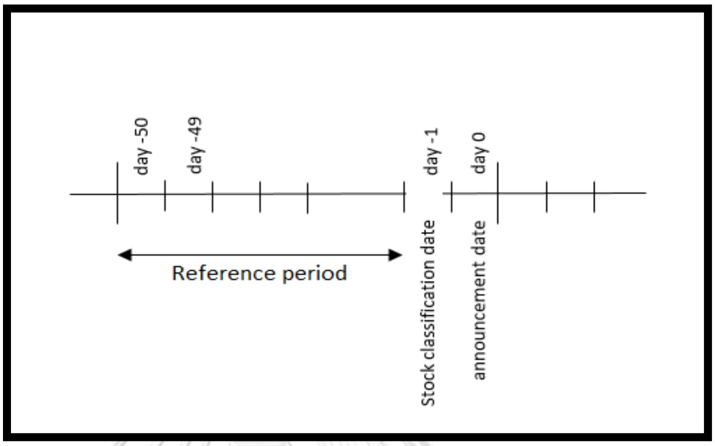

Figure 6. Time sequence for hypothesis 5.

4.3 Control Variable, Regression Analysis and Robustness Check

4.3.1 Control for Duplicate Select by Buy and Sell Volume

According to our methodology, in the same interval, there is a possibility that the stock with abnormal buy volumes is the same stock that has abnormal sell volumes. This issue may make our result hard to interpret. To control for this possibility, we will group stock into 9 groups as shown in Figure 2. Next, instead of taking a long position in all high buy (sell) volume, we take the position only in stocks that are not selected by sell (buy) volume as the high volume. Therefore, our samples are consisting of stock in group E and H (A and B). Same for short position, instead of taking a short position in all low buy (sell) volume, we take the position only in stocks that are not selected by sell (buy) volume as the low volume. Therefore, our samples are consisting of stock in group D and F (G and H). Then we perform the same analysis as in section 4.1 and 4.2. For hypothesis 2 we will use t-test to test that our new portfolios return from this section are significantly different from each other and from the return of three portfolios in Section 4.1 and 4.2. The summary of pairs of volume that we test showed in Figure 7.

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NO. (i)	Long	Short
1	High Total Volume (HT)	Low Total Volume (LT)
2	High Buy Volume (HB)	Low Buy Volume (LB)
3	High Sell Volume (HS)	Low Sell Volume (LS)
4	HBNHS	LBNLS
5	HSNHB	LSNLB
6	HBLS	LBHS

Portfolio in section 4.1 and 4.2

Figure 7. Summary of pair of volume that we test for hypothesis 1 and 2.

4.3.2 Regression Analysis to Control Others Possibly Factors

First, we address the possible factor that could affect return as following.

4.3.2.1 Interactions of Stock Returns and Trading Volume

Many past literatures have studied the correlation between stock return and trading volume. Epps (1975) found that bull (bear) markets tend to have large (small) trading volume. Wang (1994) documented that extreme short-term stock return, both positive and negative, will tend to keep their direction if they are associated with large trading volumes. Lee and Swaminathan (2002) showing that the momentum strategies are making more profit if a stock has high volume. These mean our result can be part of past return. To deal with this issue, at every formation date, we calculate variable for each long and short portfolio. For short-term interaction of portfolio i at formation date t, we calculate as follow:

$$STI_{i,t} = \frac{R_{i,t} - \bar{R}_{of\ every\ stock,t}}{SDR_{of\ every\ stock\ ,t}} \tag{4}$$

where $R_{i,t}$ is the return of portfolio i at formation date t; $\bar{R}_{of\ every\ stock,t}$ and $SDR_{of\ every\ stock\ ,t}$ are the mean and standard deviation, respectively, of return for every stock at formation date i. For mid-term interaction, we calculate as follow:

$$MTI_{i,t} = \frac{R_{i|t-49,t-1} - \bar{R}_{of\ every\ stock|t-49,t-1}}{SDR_{of every\ stock\ return|t-49,t-1}} \tag{5}$$

where $R_{i|t-49,t}$ is 49 day return of portfolio i at one day before formation date t; $\bar{R}_{of\ every\ stock|t-49,t}$ and $SDR_{of every\ stock\ return|t-49,t}$ are the mean and standard deviation, respectively, of 49 day return for every stock at one day before formation date i.

4.3.2.2 Systematic Risk

Because higher systematic risk results in higher expected return, so it could be the case that our result is affected by high systematic risk stock. To eliminate this possibility, we applied the market model to measure $\beta_{i,t}$, which is the systematic risk of portfolio i at date T as follow:

$$R_{i,T,t} = \alpha_{i,T,t} + \beta_{i,T,t} R_{m,T,t} + \varepsilon_{i,T,t} \tag{6}$$

where T=0 at every formation date t and T= -49 to 0; $R_{i,T,t}$is the return of portfolio i at time T of formation date t; $R_{m,T,t}$is the return of market at time T of formation date t. Noted $\beta_{i,0,t} = \beta_{i,t}$

4.3.2.3 Regression Equation

According to Blume, Easley et al. (1994), trading volume properties of the large firm will differ from those of the small firm. Therefore, we will include size factor ($SIZE_{i,t}$) which is the average year-end market cap of every stocks in portfolio into our regression equation. Next, we get the following regression equation:

4.3.2.3.1 Regression Equation of Hypothesis 1 and 2

Recall that the strategies that we test are shown in Figure 7. For strategies one, two and three, the regression equation is

$$\begin{aligned} R^b{}_{i,t} &= \left(\theta_0 + \theta_1 H_{i,t} + \textstyle\sum_{y=1}^{Y} \theta_{i,y,t}\, Control_{i,y,t}\right) * Totvol_{i,t} \\ &+\left(\sigma_0 + \sigma_1 H_{i,t} + \textstyle\sum_{y=1}^{Y} \sigma_{i,y,t}\, Control_{i,y,t}\right) * Buyvol_{i,t} \\ &+\left(\alpha_0 + \alpha_1 H_{i,t} + \textstyle\sum_{y=1}^{Y} \alpha_{i,y,t}\, Control_{i,y,t}\right) * Sellvol_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where $R^b{}_{i,t}$ is the returns of a stock or portfolio i if being held for b day since formation date t; $H_{i,t}$ is the dummy variable and equal to 1 if in formation date t a stock or portfolio i is classified as high volumes otherwise it is equal to zero which mean it is classified as low volume;

$Totvol_{i,t}$, $Buyvol_{i,t,}$ and $Sellvol_{i,t}$ are the dummy variable and will be 1 if in formation date t a stock or portfolio i is classified as total volume, buy volume and sell volume respectively; $Control_{i,y,t}$ is control variable type y at formation date t of stock or portfolio i. While for strategies four and five, the regression equation is

$$R^b{}_{i,t} = \emptyset_0 + \emptyset_1 HBNHS_{i,t} + \emptyset_2 LBNLS_{i,t} + \emptyset_3 HSNHB_{i,t} + \sum_{y=1}^{Y} \gamma_{i,y,t}\, Control_{i,y,t} + \varepsilon_{i,t} \tag{8}$$

where $R^b{}_{i,t}$ is the returns of a stock or portfolio i if being held for b day since formation date t; $HBNHS_{i,t}, LBNLS_{i,t}$ and $HSNHB_{i,t}$ are the dummy variable and will be 1 if in formation date t a stock i is classified as high buy volumes but not high sell volumes, low buy volumes but not low sell volumes and high sell volume but not high buy volumes respectively otherwise they are equal to zero which mean the observation is classified as low sell volumes but not low buy volumes; $Control_{i,y,t}$ is control variable type y at formation date t of stock i. While for strategies six and seven, the regression equation is

$$R^b{}_{i,t} = \delta_0 + \delta_1 HBLS_{i,t} + \sum_{y=1}^{Y} \gamma_{i,y,t}\, Control_{i,y,t} + \varepsilon_{i,t} \tag{9}$$

where $R^b{}_{i,t}$ is the returns of a stock or portfolio i if being held for b day since formation date t; $HBLS_{i,t}$ is the dummy variable and will be 1 if in formation date t a stock i is classified as high buy volumes with low sell volumes otherwise it is equal to zero which mean it is classified as low buy volume with high sell volumes; $Control_{i,y,t}$ is control variable type y at formation date t of stock i. Noted that the graphic of variable that we use in equation 8 and 9 is shown in Figure 2.

4.3.2.3.2 Regression Equation of Hypothesis 3 and 4

The conditions that we test are shown in Figure 8. For condition one two and three, the regression equation is

$$\begin{aligned} R^b{}_{i,t} &= \left(\pi_0 + \pi_1 HUnshort_{i,t} + \textstyle\sum_{y=1}^{Y} \pi_{i,y,t}\, Control_{i,y,t}\right) * Totvol_{i,t} \\ &\quad + \left(\pi_2 + \pi_3 HUnshort_{i,t} + \textstyle\sum_{y=1}^{Y} \pi_{i,y,t}\, Control_{i,y,t}\right) * Buyvol_{i,t} \\ &\quad + \left(\pi_4 + \pi_5 HUnshort_{i,t} + \textstyle\sum_{y=1}^{Y} \pi_{i,y,t}\, Control_{i,y,t}\right) * Sellvol_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{9}$$

where $R^b{}_{i,t}$ is the returns of a stock or portfolio i if being held for b day since formation date t; $HUnshort_{i,t}$ is the dummy variable and equal to 1 if in formation date t a stock or portfolio i cannot be shorted and also classified as high volumes otherwise it is equal to zero which mean it is classified as high volumes and can be shorted; while $Totvol_{i,t}$, $Buyvol_{i,t,}$ and $Sellvol_{i,t}$ are the dummy variable and equal to 1 if in formation date t a stock or portfolio i is classified by total volume, buy volume and sell volume respectively; $Control_{i,y,t}$ is control variable type y at formation date t of stock i. For condition four and five, the regression equation is

$$\begin{aligned} R^b{}_{i,t} &= \mu_0 + \mu_1 HBNHSunshort_{i,t} + \mu_2 HSNHBunshort_{i,t} + \mu_3 HBNHSshort_{i,t} \\ &\quad + \textstyle\sum_{y=1}^{Y} \gamma_{i,y,t}\, Control_{i,y,t} + \varepsilon_{i,t} \end{aligned} \tag{10}$$

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where $R^b{}_{i,t}$ is the returns of a stock or portfolio i if being held for b day since formation date t; $HBNHSunshort_{i,t}, HSNHBunshort_{i,t}$ and $HSNHBshort_{i,t}$ are the dummy variable and will be 1 if in formation date t a stock i cannot be shorted and also classified as high buy volumes but not high sell volumes stock, cannot be shorted and also classified as high sell volumes but not high buy volumes stock, can be shorted and also classified as high buy volumes but not high sell volumes stock respectively otherwise it is "shortable" stock from high sell volumes but not high buy volumes group; $Control_{i,y,t}$ is control variable type y at formation date t of stock i. For condition six and seven, the regression equation is

$$R^b{}_{i,t} = \rho_0 + \rho_1 HBLSunshort_{i,t} + \rho_2 LBHSunshort_{i,t} + \rho_3 HBLSshort_{i,t} + \sum_{y=1}^{Y} \gamma_{i,y,t}\, Control_{i,y,t} + \varepsilon_{i,t} \quad (11)$$

where $R^b{}_{i,t}$ is the returns of a stock or portfolio i if being held for b day since formation date t; $HBLSunshort_{i,t}, LBHSunshort_{i,t}$ and $HBLSshort_{i,t}$ are the dummy variable and will be 1 if in formation date t a stock i cannot be shorted and also classified as high buy volumes with low sell volumes, cannot be shorted and also classified as low buy volumes with high sell volumes, can be shorted and also classified as high buy volumes with low sell volumes respectively otherwise it is "shortable" stock from as low buy volumes with high sell volumes group; $Control_{i,y,t}$ is control variable type y at formation date t of stock i.

NO. (i)	Condition
1	High Total Volume (HT)
2	High Buy Volume (HB)
3	High Sell Volume (HS)
4	HBNHS
5	HSNHB
6	HBLS
7	LBHS

Figure 8. Summary of condition that we test for hypothesis 4 and 5.

4.3.3 Alternative Method for Classify Abnormal Volume

4.3.3.1 Unequal Weight Ranking

In section 3, giving each day in trading interval an equal weight, the rank of volumes at formation date is defined by comparing it with other day in trading interval. However, if the volumes are uptrend (downtrend), using an equal weight of past volumes could result in misclassification of stock as high (low) instead of normal volume stock. For example, a stock has a volume profile as shown in Figure 9. Giving twenty days trading interval, a stock would be classified as high volume if we give each day an equal weight because volume in day 0 is ranked in 1st 2nd place. Anywise, we can see that the volumes amounts are not abnormal high. So, to prevent these potential scenarios, we then use weight schemes which will give more weight based on how closer the day to the formation date (the closer the day is the higher the weights are). To using weight schemes to classify stock, first, calculate $w_t(n)$ (relative weight of volume in day t) using the following equation:

$$w_t(n) = 1 + \frac{(n-1)(t-1)}{T-1} \tag{13}$$

where T is the length of reference period which is 49 in our case; t is the day of reference period (t=1 is first day of reference period and t= T is last day of reference period) and n is the number of times that the weight at the last day of reference period is greater than the weight at the first day of reference period (Noted that classification in section 3 is the same with this method if we use n =1). Next, we will classify a stock j as high (low) volume stock if

$$\sum_{t=1}^{49} 1_{(V_j^{50}<V_j^t)} \frac{w_t(n)}{\sum_{T=1}^{49} w_T(n)} < 10\% \quad \left(\sum_{t=1}^{49} 1_{(V_j^{50}>V_j^t)} \frac{w_t(n)}{\sum_{T=1}^{49} w_T(n)} < 10\%\right) \tag{14}$$

Where V_j^t is the stock j's volumes on the t day of a trading interval (t = 50 referring to the formation date). The equation is simply state that at any t if $V_j^{50} < V_j^t \left(V_j^{50} > V_j^t\right)$ the value at that day is $\frac{w_t(n)}{\sum_{T=1}^{49} w_T(n)}$. In addition, if total value in that reference period is < 0.1, a stock is classified as high (low) volume stock otherwise it will be classified as normal volume stock. Finally, we will use this method with n equal to 8 to classify stocks and check whether the result of each hypothesis still significant or not.

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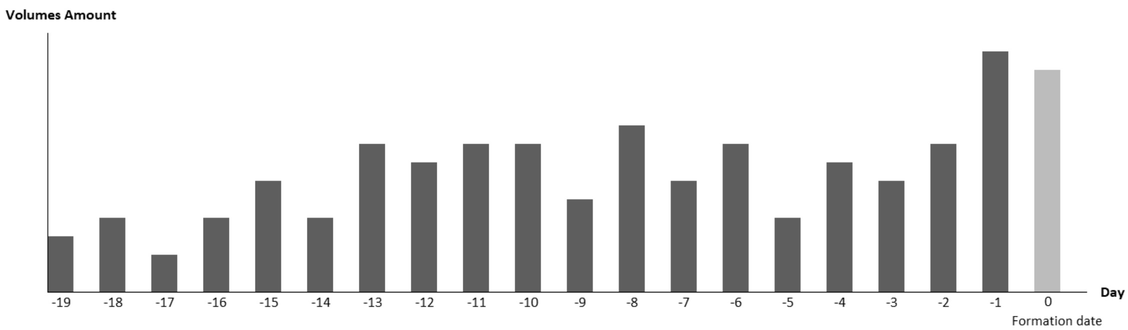

Figure 9. Example case of misclassification.

CHAPTER 5

EMPIRICAL RESULTS

5.1 Main hypothesis, Return Predictability of Each Type of Volume

We started by investigating whether the strategy that long abnormal high volumes and short abnormal low volumes can provide returns which are significantly not equal to zero. Table 1, Table 2 and Table 3 display the summary statistics of each group, we can see that on average, high volume tends to provide higher return compare to low volume group except for 1 day return of sell volumes classification. Anywise, considering the significant of the result, we found that zero portfolio method show no significant result. However, reference portfolio method shows some significant result. Figure 10 and 11 display proportion of interval sets that give significantly positive returns, significantly negative returns, and no significant result for both n=1 and n=8 criteria. In addition, the results are shown at 95% confident from reference portfolio method over 1, 3, 5, 10, 20 and 50 trading day after the formation date. As can be seen from these tables, for both n=1 and n=8 criteria, buy volumes and sell volumes provides significant result even though we shift the formation date. This means the strategy will work better if we give each stock equal weight instead of giving each day equal weight. Furthermore, the results show that buy volumes and sell volumes are better than total volumes in terms of predictability. While results from abnormal high total volumes strategy are mixed among the set of intervals, the results from abnormal high buy volumes show an upward stock price direction after the portfolio formation, especially when the stock is not in abnormal high sell volumes group. Also, the results from abnormal sell volumes show a downward stock price direction after the portfolio formation, especially when the stock is not in abnormal high buy volumes group. And, as can be seen from Figure 12 and Figure 13 that buy volume strategy gives a higher return in terms of average, upper bound and lower bound. However, the results are consistent only in one-day return prediction. To sum up, even though abnormal total volume may not be able to predict future returns in Thailand, we find that the rest of volumes can. This implies that volume components reveal some aspect of trading. Notes that the directions of results from both n=1 and n=8 case are the same, which confirm the robustness of our results.

Table 1

From 2012 to May 2018, we create 30 nonoverlapping trading intervals and get 30 formation date. In each formation date, we use both buy and sell types of volume to sort stock into high buy not high sell, low buy not low sell, high sell not high buy and low sell not low buy group. After we assign stocks into each group for all the formation date, we then get 1 data set to test the hypothesis. However, for robustness of the result, we create nonoverlapping trading intervals all over again but with different start date until we get 51 dataset of different star date and every day of testing period have been used as formation date. The table reports the statistic number of the stocks that selected into each group in each data set. The table also report total volume abnormally (Total volume at formation date / Average total volume in reference) and return of every stock that been selected into that group from 51 data sets.

	Average	SD	Max	Min	Average	SD	Max	Min
	HBNHS				**HSNHB**			
Number of stocks per data set	542.3	48.9	640.0	444.0	536.7	68.2	738.0	414.0
Total volume abnormally	2.20	8.60	1267.16	0.01	2.25	7.12	1110.34	0.02
1 Day Return	0.12%	2.67%	29.86%	-24.88%	0.04%	2.63%	29.67%	-26.97%
3 Day Return	0.23%	4.47%	73.08%	-45.77%	0.18%	4.62%	104.52%	-52.86%
5 Day Return	0.32%	5.71%	91.27%	-45.77%	0.27%	5.82%	104.39%	-50.69%
10 Day Return	0.51%	7.98%	132.24%	-52.69%	0.59%	8.30%	214.56%	-63.17%
20 Day Return	1.01%	11.35%	241.18%	-65.60%	1.26%	12.75%	483.33%	-73.46%
50 Day Return	2.24%	20.70%	684.31%	-78.85%	2.65%	21.19%	874.36%	-78.02%
	LBNLS				**LSNLB**			
Number of stocks per data set	985.7	72.1	1151.0	815.0	986.6	105.5	1194.0	688.0
Total volume abnormally	0.33	0.96	163.93	0.00	0.39	14.93	2444.87	0.00
1 Day Return	-0.03%	2.05%	30.09%	-25.24%	0.05%	2.06%	29.95%	-25.24%
3 Day Return	-0.08%	3.34%	70.31%	-29.60%	0.11%	3.76%	103.45%	-28.27%
5 Day Return	-0.14%	4.28%	80.47%	-37.82%	0.14%	5.17%	380.71%	-39.75%
10 Day Return	-0.30%	6.32%	111.72%	-48.00%	0.19%	7.63%	425.22%	-57.60%
20 Day Return	-0.35%	9.19%	148.67%	-71.68%	0.41%	11.69%	656.68%	-69.48%
50 Day Return	-0.78%	15.31%	203.91%	-73.68%	0.97%	19.46%	635.91%	-67.92%

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Table 2

From 2012 to May 2018, we create 30 nonoverlapping trading intervals and get 30 formation date. In each formation date, we use both buy and sell types of volume to sort stock into nine group of stock. After we assign stocks into each group for all the formation date, we then get 1 data set to test the hypothesis. However, for robustness of the result, we create nonoverlapping trading intervals all over again but with different start date until we get 51 dataset of different star date and every day of testing period have been used as formation date. The table reports the statistic number of the stocks that selected into each group in each data set. The table also report total volume abnormally (Total volume at formation date / Average total volume in reference) and return of every stock that been selected into that group from 51 data sets.

	Average	SD	Max	Min	Average	SD	Max	Min	Average	SD	Max	Min
	HBHS				**NBHS**				**LBHS**			
Number of stocks per data set	792.4	54.6	880.0	672.0	521.9	66.6	723.0	398.0	15.5	4.4	26.0	6.0
Total volume abnormally	7.10	16.62	1937.20	0.05	2.27	7.22	1110.34	0.03	1.58	1.33	16.48	0.02
1 Day Return	-0.05%	3.83%	31.93%	-29.95%	0.03%	2.65%	29.67%	-26.97%	0.15%	1.91%	18.11%	-9.72%
3 Day Return	0.10%	6.14%	118.52%	-50.49%	0.18%	4.66%	104.52%	-52.86%	0.19%	3.48%	31.51%	-15.29%
5 Day Return	0.15%	7.57%	131.78%	-64.60%	0.27%	5.88%	104.39%	-50.69%	0.15%	4.05%	40.00%	-19.32%
10 Day Return	0.44%	10.94%	514.13%	-63.98%	0.59%	8.38%	214.56%	-63.17%	0.22%	5.41%	48.04%	-22.60%
20 Day Return	1.12%	15.96%	634.40%	-68.40%	1.28%	12.87%	483.33%	-73.46%	0.20%	7.36%	49.66%	-31.51%
50 Day Return	2.65%	26.37%	1013.60%	-75.00%	2.68%	21.39%	874.36%	-78.02%	1.17%	12.73%	94.95%	-43.06%
	HBNS				**NBNS**				**LBNS**			
Number of stocks per data set	527.7	48.2	623.0	430.0	7990.6	138.0	8319.0	7696.0	970.9	72.6	1138.0	803.0
Total volume abnormally	2.22	8.71	1267.16	0.01	0.76	4.34	1764.74	0.00	0.31	0.94	163.93	0.00
1 Day Return	0.12%	2.69%	29.86%	-24.88%	0.06%	2.59%	380.71%	-30.07%	-0.03%	2.05%	30.09%	-25.24%
3 Day Return	0.23%	4.51%	73.08%	-45.77%	0.14%	4.48%	413.35%	-59.73%	0.01%	4.31%	383.58%	-31.93%
5 Day Return	0.32%	5.76%	91.27%	-45.77%	0.25%	5.86%	431.16%	-58.97%	0.03%	5.42%	428.36%	-37.82%
10 Day Return	0.52%	8.04%	132.24%	-52.69%	0.47%	8.45%	472.70%	-70.88%	0.11%	7.85%	479.10%	-48.31%
20 Day Return	1.02%	11.43%	241.18%	-65.60%	0.86%	12.46%	649.26%	-77.14%	0.25%	11.37%	622.39%	-71.68%
50 Day Return	2.24%	20.85%	684.31%	-78.85%	1.88%	21.45%	1075.96%	-78.98%	0.79%	18.60%	653.73%	-73.68%
	HBLS				**NBLS**				**LBLS**			
Number of stocks per data set	15.3	3.5	27.0	8.0	972.1	104.8	1176.0	673.0	623.8	84.4	834.0	422.0
Total volume abnormally	1.42	2.17	42.94	0.05	0.37	15.04	2444.87	0.00	0.14	0.52	68.38	0.00
1 Day Return	0.00%	1.99%	15.20%	-20.39%	0.05%	2.06%	29.95%	-25.24%	-0.02%	2.28%	30.08%	-28.39%
3 Day Return	0.17%	3.22%	29.73%	-19.83%	0.11%	3.77%	103.45%	-28.27%	-0.01%	4.17%	70.12%	-43.75%
5 Day Return	0.17%	4.37%	40.00%	-20.39%	0.14%	5.19%	380.71%	-39.75%	-0.01%	5.87%	380.60%	-47.02%
10 Day Return	0.09%	5.86%	48.04%	-26.04%	0.19%	7.67%	425.22%	-57.60%	0.05%	8.54%	449.25%	-56.65%
20 Day Return	0.14%	8.42%	101.00%	-39.39%	0.41%	11.74%	656.68%	-69.48%	0.09%	13.03%	629.73%	-73.08%
50 Day Return	1.61%	14.85%	176.56%	-36.54%	0.95%	19.53%	635.91%	-67.92%	0.32%	20.75%	653.73%	-77.83%

Table 3

From 2012 to May 2018, we create 30 nonoverlapping trading intervals and get 30 formation date. In each formation date, we use each type of volume to sort stock into high normal or low group. After we assign stocks into each group for all the formation date, we then get 1 data set to test the hypothesis. However, for robustness of the result, we create nonoverlapping trading intervals all over again but with different start date until we get 51 dataset of different star date and every day of testing period have been used as formation date. The table reports the statistic number of the stocks that selected into each group in each data set. The table also report total volume abnormally (Total volume at formation date / Average total volume in reference) and return of every stock that been selected into that group from 51 data sets.

		Total Volume				**Buy Volume**				**Sell Volume**			
		Average	SD	Max	Min	Average	SD	Max	Min	Average	SD	Max	Min
High	Number of stocks per data set	1320.7	79.1	1498.0	1126.0	1334.7	84.8	1501.0	1127.0	1329.1	96.3	1573.0	1095.0
	Total volume abnormally	5.73	22.29	2444.87	0.03	5.11	14.13	1937.20	0.01	5.14	13.81	1937.20	0.02
	1 Day Return	0.00%	3.45%	31.93%	-29.95%	0.02%	3.41%	31.93%	-29.95%	-0.02%	3.40%	31.93%	-29.95%
	3 Day Return	0.13%	5.61%	118.52%	-52.86%	0.15%	5.52%	118.52%	-50.49%	0.13%	5.57%	118.52%	-52.86%
	5 Day Return	0.21%	6.96%	131.78%	-64.60%	0.22%	6.88%	131.78%	-64.60%	0.20%	6.92%	131.78%	-64.60%
	10 Day Return	0.49%	9.99%	514.13%	-63.98%	0.47%	9.84%	514.13%	-63.98%	0.50%	9.96%	514.13%	-63.98%
	20 Day Return	1.14%	14.57%	634.40%	-73.46%	1.07%	14.26%	634.40%	-68.40%	1.18%	14.74%	634.40%	-73.46%
	50 Day Return	2.58%	24.51%	1013.60%	-78.02%	2.48%	24.23%	1013.60%	-78.85%	2.65%	24.41%	1013.60%	-78.02%
Normal	Number of stocks per data set	9457.7	151.0	9767.0	9146.0	9484.5	147.0	9785.0	9187.0	9489.2	151.0	9770.0	9193.0
	Total volume abnormally	0.74	0.56	9.66	0.00	0.80	6.48	2444.87	0.00	0.79	4.51	1764.74	0.00
	1 Day Return	0.06%	2.54%	380.71%	-30.07%	0.06%	2.54%	380.71%	-30.07%	0.05%	2.54%	380.71%	-30.07%
	3 Day Return	0.15%	4.48%	413.35%	-59.73%	0.14%	4.42%	413.35%	-59.73%	0.14%	4.46%	413.35%	-59.73%
	5 Day Return	0.24%	5.84%	431.16%	-58.97%	0.24%	5.80%	431.16%	-58.97%	0.23%	5.81%	431.16%	-58.97%
	10 Day Return	0.45%	8.39%	479.10%	-70.88%	0.44%	8.37%	472.70%	-70.88%	0.43%	8.37%	479.10%	-70.88%
	20 Day Return	0.84%	12.36%	656.68%	-77.14%	0.83%	12.41%	656.68%	-77.14%	0.80%	12.30%	649.26%	-77.14%
	50 Day Return	1.84%	21.25%	1075.96%	-78.98%	1.83%	21.26%	1075.96%	-78.98%	1.79%	21.15%	1075.96%	-78.98%
Low	Number of stocks per data set	1650.3	180.2	2098.0	1231.0	1609.5	136.7	1913.0	1390.0	1610.4	175.5	2028.0	1110.0
	Total volume abnormally	0.16	0.12	0.92	0.00	0.26	0.82	163.93	0.00	0.29	11.70	2444.87	0.00
	1 Day Return	-0.01%	2.10%	30.08%	-28.39%	-0.02%	2.14%	30.09%	-28.39%	0.02%	2.15%	30.08%	-28.39%
	3 Day Return	-0.01%	3.82%	70.31%	-43.75%	0.01%	4.24%	383.58%	-43.75%	0.06%	3.92%	103.45%	-43.75%
	5 Day Return	0.01%	5.23%	380.60%	-47.02%	0.02%	5.58%	428.36%	-47.02%	0.08%	5.45%	380.71%	-47.02%
	10 Day Return	0.07%	7.84%	449.25%	-57.60%	0.09%	8.10%	479.10%	-56.65%	0.14%	8.00%	449.25%	-57.60%
	20 Day Return	0.15%	12.02%	629.73%	-73.08%	0.19%	12.01%	629.73%	-73.08%	0.29%	12.23%	656.68%	-73.08%
	50 Day Return	0.48%	19.27%	653.73%	-77.83%	0.62%	19.42%	653.73%	-77.83%	0.72%	19.98%	653.73%	-77.83%

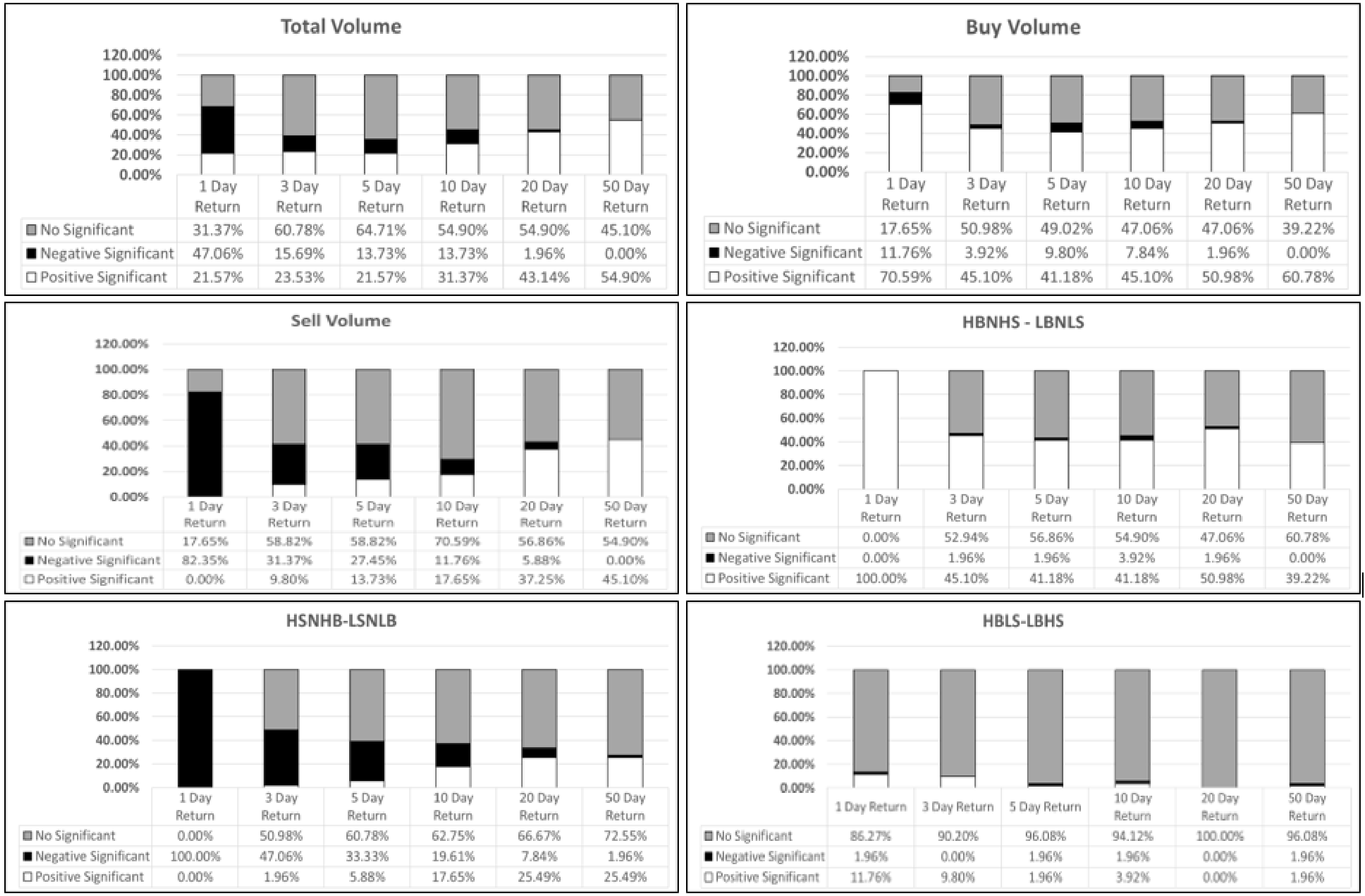
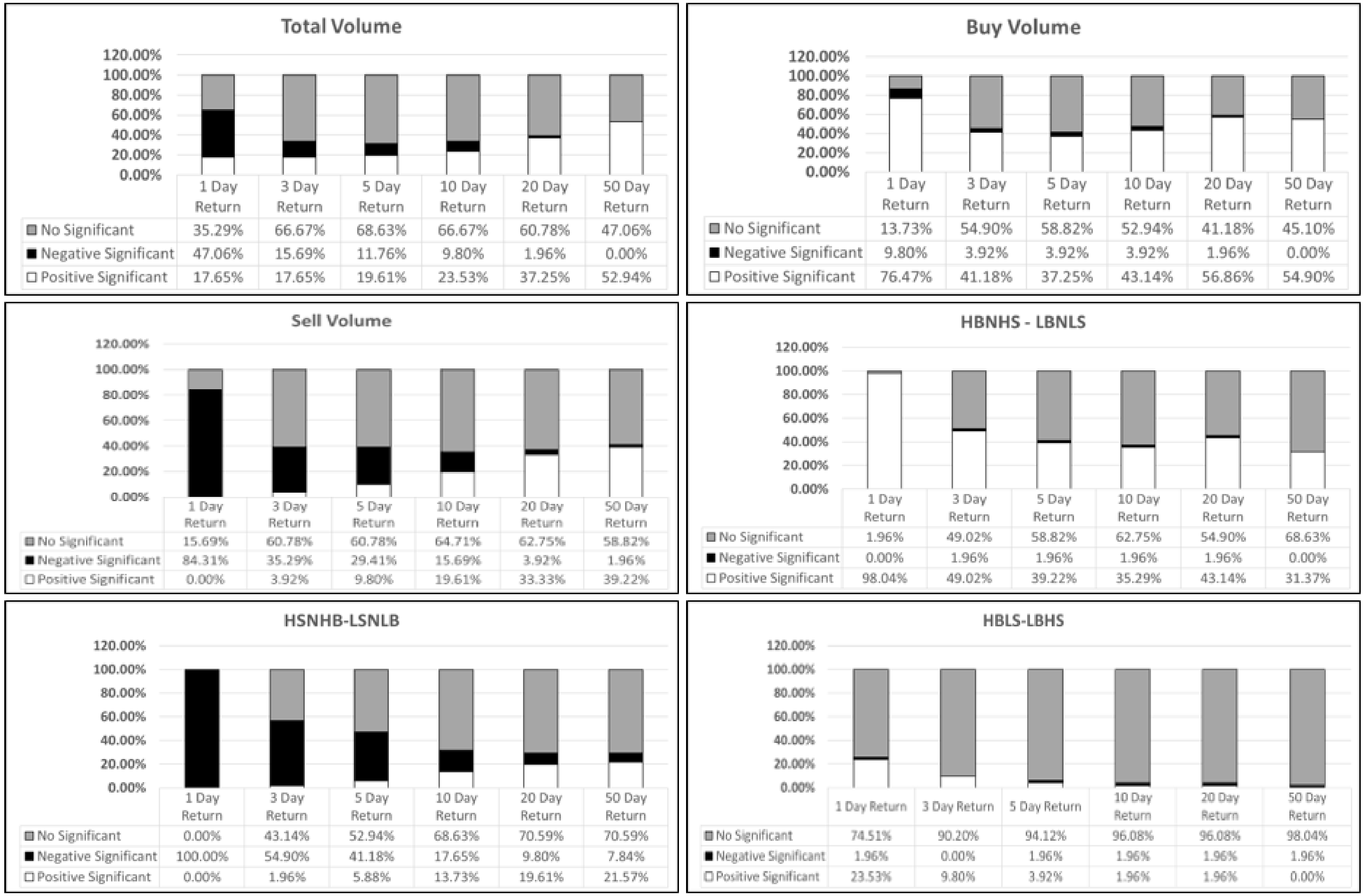


Figure 10
In each type of volume group, we construct portfolio formation held for 1, 3, 5, 10, 20 and 50days by reference portfolio method selected by n=1 stock classification. From 51 interval sets in totals, with 95% significant, these graph display proportion of interval sets that give significantly positive returns, significant negative returns and no significant returns in each type of volume strategy.



Total Volume

	1 Day Return	3 Day Return	5 Day Return	10 Day Return	20 Day Return	50 Day Return
No Significant	35.29%	66.67%	68.63%	66.67%	60.78%	47.06%
Negative Significant	47.06%	15.69%	11.76%	9.80%	1.96%	0.00%
Positive Significant	17.65%	17.65%	19.61%	23.53%	37.25%	52.94%

Buy Volume

	1 Day Return	3 Day Return	5 Day Return	10 Day Return	20 Day Return	50 Day Return
No Significant	13.73%	54.90%	58.82%	52.94%	41.18%	45.10%
Negative Significant	9.80%	3.92%	3.92%	3.92%	1.96%	0.00%
Positive Significant	76.47%	41.18%	37.25%	43.14%	56.86%	54.90%

Sell Volume

	1 Day Return	3 Day Return	5 Day Return	10 Day Return	20 Day Return	50 Day Return
No Significant	15.69%	60.78%	60.78%	64.71%	62.75%	58.82%
Negative Significant	84.31%	35.29%	29.41%	15.69%	3.92%	1.96%
Positive Significant	0.00%	3.92%	9.80%	19.61%	33.33%	39.22%

HBNHS - LBNLS

	1 Day Return	3 Day Return	5 Day Return	10 Day Return	20 Day Return	50 Day Return
No Significant	1.96%	49.02%	58.82%	62.75%	54.90%	68.63%
Negative Significant	0.00%	1.96%	1.96%	1.96%	1.96%	0.00%
Positive Significant	98.04%	49.02%	39.22%	35.29%	43.14%	31.37%

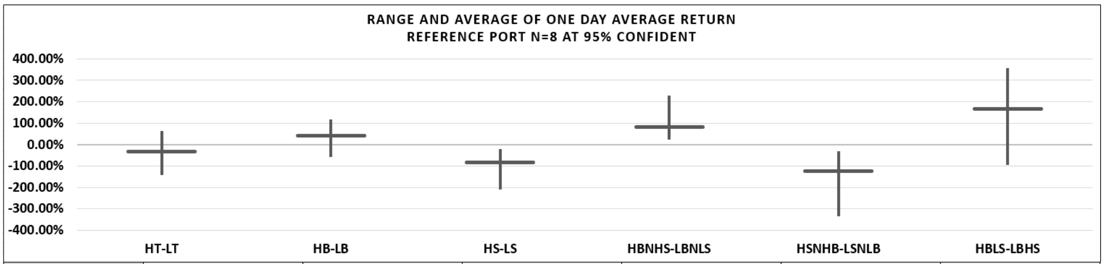
HSNHB-LSNLB

	1 Day Return	3 Day Return	5 Day Return	10 Day Return	20 Day Return	50 Day Return
No Significant	0.00%	43.14%	52.94%	68.63%	70.59%	70.59%
Negative Significant	100.00%	54.90%	41.18%	17.65%	9.80%	7.84%
Positive Significant	0.00%	1.96%	5.88%	13.73%	19.61%	21.57%

HBLS-LBHS

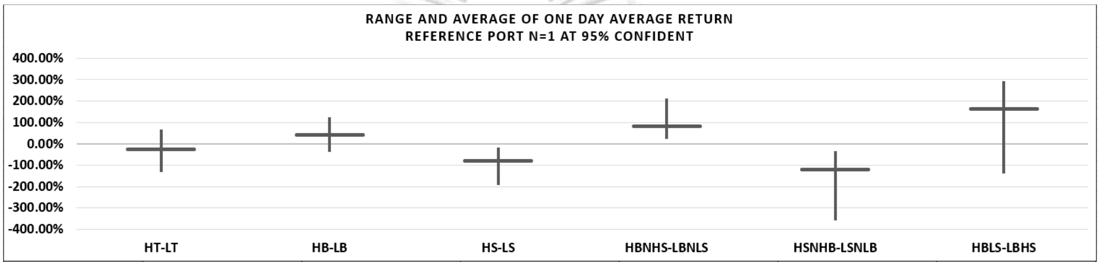
	1 Day Return	3 Day Return	5 Day Return	10 Day Return	20 Day Return	50 Day Return
No Significant	74.51%	90.20%	94.12%	96.08%	96.08%	98.04%
Negative Significant	1.96%	0.00%	1.96%	1.96%	1.96%	1.96%
Positive Significant	23.53%	9.80%	3.92%	1.96%	1.96%	0.00%

Figure 11
In each type of volume group, we construct portfolio formation held for 1, 3, 5, 10, 20 and 50days by reference portfolio method selected by n=8 stock classification. From 51 interval sets in totals, with 95% significant, these graph display proportion of interval sets that give significantly positive returns, significant negative returns and no significant returns in each type of volume strategy



	HT-LT	HB-LB	HS-LS	HBNHS-LBNLS	HSNHB-LSNLB	HBLS-LBHS
Upper Bound (Annualized)	65.25%	116.50%	-20.70%	228.00%	-30.75%	357.50%
Average (Annualized)	-30.12%	43.28%	-80.35%	83.76%	-121.40%	168.98%
Lower Bound (Annualized)	-143.00%	-57.75%	-208.75%	23.50%	-333.75%	-96.15%

Figure 12 Range and average of one-day average annual return from interval sets that significant at 95% confident using n=1 criteria to classify stock



	HT-LT	HB-LB	HS-LS	HBNHS-LBNLS	HSNHB-LSNLB	HBLS-LBHS
Upper Bound (Annualized)	66.50%	125.00%	-16.03%	213.50%	-33.30%	291.50%
Average (Annualized)	-25.14%	45.02%	-76.72%	84.67%	-117.29%	163.92%
Lower Bound (Annualized)	-132.50%	-38.75%	-193.50%	24.00%	-357.00%	-137.50%

Figure 13 Range and average of one-day average annual return from interval sets that significant at 95% confident using n=8 criteria to classify stock

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From now on our research will focus on reference portfolio method. To confirm our results that strategy from each type of volume predicts a different outcome, we run a regression to test return between each type of volume whether they give the same return or not. Table 4 displays proportion of interval sets that significantly provides different returns between each strategy. The result confirms our hypothesis that each type of volumes predicts different future returns. Also, Table 5 and 6 show that buy volumes strategy is confirming to give higher returns compare to other types of volumes and sell volume strategy is confirming to give lower returns compare to other types of volumes for 1-day returns. These results confirm our hypothesis that each type of volume provide different information content.

5.2 Economic Profitability of the Strategies

To infer whether positive economic profit could be generated by using strategies that we test. First, recall that the returns using in this study come from closing daily prices, this strategy should give the profit to investors if their orders are not large enough to move the closing price far away from where they were. Second, even though in this study we not consider transaction fee, given 250 trading day per year, the results have shown that average returns of our strategy are 0.34% from buy volume and 0.47% from sell volume. This mean that if investors pay commission fee less than 0.17%, the investors can still make a profit from this strategy.

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Table 4

In each type of volume group, we construct portfolio formation held for 1, 3, 5, 10, 20 and 50days by zero portfolio method and reference portfolio method selected by both n=1 and n=8 stock classification. From 51 interval sets in totals, this table display proportion of interval sets that give significantly different in returns between each volume group.

		(HT-LT)-(HB-LB)S≠0	(HT-LT)-(HS-LS)S≠0	(HB-LB)-(HS-LS)S≠0	(HBNHS-LBNLS)-(HSNHB-LSNLBS≠0
n=1	1 Day Return	98.04%	94.12%	100.00%	100.00%
	3 Day Return	15.69%	1.96%	45.10%	62.75%
	5 Day Return	5.88%	0.00%	29.41%	50.98%
	10 Day Return	1.96%	0.00%	21.57%	37.25%
	20 Day Return	1.96%	0.00%	13.73%	39.22%
	50 Day Return	1.96%	0.00%	5.88%	29.41%
n=8	1 Day Return	98.04%	98.04%	100.00%	100.00%
	3 Day Return	15.69%	9.80%	56.86%	78.43%
	5 Day Return	7.84%	3.92%	39.22%	56.86%
	10 Day Return	0.00%	0.00%	21.57%	39.22%
	20 Day Return	0.00%	0.00%	13.73%	37.25%
	50 Day Return	0.00%	0.00%	5.88%	23.53%

Table 5

In each type of volume group, we construct portfolio formation held for 1, 3, 5, 10, 20 and 50days by zero portfolio method and reference portfolio method selected by both n=1 and n=8 stock classification. We test strategy from each volume group by minus return from volume group x by return from volume group y whether they are equal or not (x-y=0). From 51 interval sets in totals, this table display proportion of interval sets that strategy x has higher return compared to strategy y.

		(HT-LT)-(HB-LB)S≠0	(HT-LT)-(HS-LS)S≠0	(HB-LB)-(HS-LS)S≠0	(HBNHS-LBNLS)-(HSNHB-LSNLBS≠0
n=1	1 Day Return	0.00%	94.12%	100.00%	100.00%
	3 Day Return	0.00%	1.96%	45.10%	60.78%
	5 Day Return	0.00%	0.00%	27.45%	45.10%
	10 Day Return	0.00%	0.00%	19.61%	31.37%
	20 Day Return	0.00%	0.00%	11.76%	31.37%
	50 Day Return	1.96%	0.00%	1.96%	19.61%
n=8	1 Day Return	0.00%	98.04%	100.00%	100.00%
	3 Day Return	0.00%	9.80%	56.86%	76.47%
	5 Day Return	0.00%	3.92%	37.25%	50.98%
	10 Day Return	0.00%	0.00%	21.57%	37.25%
	20 Day Return	0.00%	0.00%	13.73%	29.41%
	50 Day Return	0.00%	0.00%	3.92%	17.65%

Table 6

In each type of volume group, we construct portfolio formation held for 1, 3, 5, 10, 20 and 50days by zero portfolio method and reference portfolio method selected by both n=1 and n=8 stock classification. We test strategy from each volume group by minus return from volume group x by return from volume group y whether they are equal or not (x-y=0). From 51 interval sets in totals, this table display proportion of interval sets that strategy x has lower return compared to strategy y.

		(HT-LT)-(HB-LB)S≠0	(HT-LT)-(HS-LS)S≠0	(HB-LB)-(HS-LS)S≠0	(HBNHS-LBNLS)-(HSNHB-LSNLBS≠0
n=1	1 Day Return	98.04%	0.00%	0.00%	0.00%
	3 Day Return	15.69%	0.00%	0.00%	1.96%
	5 Day Return	5.88%	0.00%	1.96%	5.88%
	10 Day Return	1.96%	0.00%	1.96%	5.88%
	20 Day Return	1.96%	0.00%	1.96%	7.84%
	50 Day Return	0.00%	0.00%	3.92%	9.80%
n=8	1 Day Return	98.04%	0.00%	0.00%	0.00%
	3 Day Return	15.69%	0.00%	0.00%	1.96%
	5 Day Return	7.84%	0.00%	1.96%	5.88%
	10 Day Return	0.00%	0.00%	0.00%	1.96%
	20 Day Return	0.00%	0.00%	0.00%	7.84%
	50 Day Return	0.00%	0.00%	1.96%	5.88%

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5.3 Possible Reasons Behind Predictability

5.3.1 Attention Grabbing Hypothesis

We started by investigating attention grabbing hypothesis. Table 8 and Table 9 display the summary statistics of each group, we can see that in long term, stock that cannot be shorted tends to provide higher return compare to stock that cannot be shorted. Anywise, Table 7 displays the statistically results from reference portfolio for both n=1 and n=8 case which more than half of the interval sets cannot proof that, in abnormal trading event, “unshortable” stocks will give a significant higher return than “shortable” stocks. Recall that the stocks which do not experience short sales tend to be affected more by visibility because new players can engage only long position. This means that attention grabbing might not be the solid conclusion for high volume return premium in Thailand.

Table 2

In each type of volume group, we construct portfolio formation held for 1, 3, 5, 10, 20 and 50days by reference portfolio method selected by both n=1 and n=8 stock classification. From 51 interval sets in totals, this table display proportion of interval sets that unshortable stock give significantly higher returns compare to shortable stock after abnormal high trading event in each type of volume strategy.

Number of Interval Set That Give Positive Return (Both Signifiacnt and Not Significant)						
Case n=1 , 90% Confident	one day return	three day return	five day return	ten day return	twenty day return	fifty day return
HTunshort-Htshort>0	21.57%	1.96%	9.80%	17.65%	13.73%	23.53%
HBunshort-Hbshort>0	11.76%	3.92%	7.84%	13.73%	13.73%	17.65%
HSunshort-Hsshort>0	29.41%	5.88%	9.80%	9.80%	15.69%	19.61%
HBNHSunshort-HBNHSshort>0	39.22%	5.88%	9.80%	5.88%	5.88%	0.00%
HSNHBunshort-HSNHBshort>0	3.92%	11.76%	13.73%	9.80%	9.80%	1.96%
HBLSunshort-HBLSshort>0	7.84%	7.84%	11.76%	5.88%	5.88%	3.92%
LBHSunshort-LBHSshort>0	7.84%	5.88%	3.92%	3.92%	3.92%	5.88%
Number of Interval Set That Give Positive Return (Both Signifiacnt and Not Significant)						
Case n=8 , 90% Confident	one day return	three day return	five day return	ten day return	twenty day return	fifty day return
HTunshort-Htshort>0	21.57%	5.88%	11.76%	17.65%	13.73%	27.45%
HBunshort-Hbshort>0	15.69%	5.88%	7.84%	9.80%	9.80%	13.73%
HSunshort-Hsshort>0	25.49%	7.84%	7.84%	15.69%	15.69%	23.53%
HBNHSunshort-HBNHSshort>0	27.45%	3.92%	9.80%	7.84%	7.84%	0.00%
HSNHBunshort-HSNHBshort>0	0.00%	3.92%	9.80%	5.88%	7.84%	7.84%
HBLSunshort-HBLSshort>0	13.73%	7.84%	11.76%	11.76%	11.76%	11.76%
LBHSunshort-LBHSshort>0	11.76%	7.84%	1.96%	1.96%	0.00%	1.96%

Table 3

From 2012 to May 2018, we create 30 nonoverlapping trading intervals and get 30 formation date. In each formation date, we use both buy and sell types of volume to sort stock into each group. Then separate stock in each group by short sell experience. After we assign stocks into each group for all the formation date, we then get 1 data set to test the hypothesis. However, for robustness of the result, we create nonoverlapping trading intervals all over again but with different start date until we get 51 dataset of different star date and every day of testing period have been used as formation date. The table reports the statistic number of the stocks that selected into each group in each data set. The table also report return of every stock that been selected into that group from 51 data sets.

		HBNHS				HSNHB			
		Average	SD	Max	Min	Average	SD	Max	Min
Unshortable	Number of stocks per data set	369.2	32.8	433.0	300.0	359.078	42.5102	486	266
	1 Day Return	0.14%	2.83%	29.86%	-24.88%	0.03%	2.73%	29.67%	-26.88%
	3 Day Return	0.28%	4.76%	73.08%	-45.77%	0.14%	4.90%	104.52%	-48.12%
	5 Day Return	0.37%	6.10%	91.27%	-45.77%	0.22%	6.14%	104.39%	-49.69%
	10 Day Return	0.55%	8.55%	132.24%	-52.69%	0.60%	8.94%	214.56%	-63.17%
	20 Day Return	1.03%	12.10%	241.18%	-57.69%	1.29%	13.97%	483.33%	-73.46%
	50 Day Return	2.41%	22.72%	684.31%	-78.85%	2.83%	23.37%	874.36%	-78.02%
Shortable	Number of stocks per data set	176.0	21.8	223.0	132.0	178.745	28.9004	251	130
	1 Day Return	0.08%	2.29%	24.62%	-20.92%	0.02%	2.38%	18.53%	-26.97%
	3 Day Return	0.09%	3.79%	33.85%	-29.92%	0.23%	3.99%	30.87%	-52.86%
	5 Day Return	0.16%	4.77%	41.67%	-31.90%	0.33%	5.08%	36.92%	-50.69%
	10 Day Return	0.37%	6.55%	49.02%	-51.16%	0.49%	6.78%	62.83%	-50.69%
	20 Day Return	0.83%	9.49%	103.60%	-65.60%	1.09%	9.71%	140.71%	-56.48%
	50 Day Return	1.43%	15.57%	144.00%	-70.51%	1.93%	15.66%	177.06%	-63.87%

		HBLS				LBHS			
		Average	SD	Max	Min	Average	SD	Max	Min
Unshortable	Number of stocks per data set	13.6	3.6	26.0	8.0	13.8	4.0	23.0	6.0
	1 Day Return	-0.04%	2.02%	15.20%	-20.39%	0.13%	1.88%	18.11%	-9.72%
	3 Day Return	0.11%	3.25%	29.73%	-19.83%	0.19%	3.50%	31.51%	-13.64%
	5 Day Return	0.14%	4.35%	40.00%	-20.39%	0.15%	4.10%	40.00%	-19.32%
	10 Day Return	-0.02%	5.86%	48.04%	-26.04%	0.26%	5.46%	48.04%	-22.60%
	20 Day Return	0.06%	8.40%	101.00%	-30.21%	0.20%	7.48%	49.66%	-31.51%
	50 Day Return	1.33%	15.04%	176.56%	-36.54%	1.30%	12.83%	94.95%	-37.20%
Shortable	Number of stocks per data set	1.7	1.2	4.0	0.0	1.6	1.2	5.0	0.0
	1 Day Return	0.35%	1.73%	8.08%	-5.34%	0.37%	2.14%	12.87%	-4.50%
	3 Day Return	0.70%	2.99%	16.16%	-3.77%	0.42%	3.70%	15.83%	-15.29%
	5 Day Return	0.56%	4.47%	18.07%	-6.54%	0.42%	4.03%	16.55%	-14.12%
	10 Day Return	1.11%	5.75%	22.03%	-16.20%	0.16%	5.57%	20.14%	-18.82%
	20 Day Return	0.87%	8.73%	24.32%	-39.39%	0.44%	6.55%	18.86%	-23.20%
	50 Day Return	4.07%	13.11%	41.73%	-25.97%	0.22%	11.91%	26.67%	-43.06%

Table 9

From 2012 to May 2018, we create 30 nonoverlapping trading intervals and get 30 formation date. In each formation date, we use each types of volume to sort stock into high volume group. Then separate stock in each group by short sell experience. After we assign stocks into each group for all the formation date, we then get 1 data set to test the hypothesis. However, for robustness of the result, we create nonoverlapping trading intervals all over again but with different start date until we get 51 dataset of different star date and every day of testing period have been used as formation date. The table reports the statistic number of the stocks that selected into each group in each data set. The table also report return of every stock that been selected into that group from 51 data sets.

		High Total Volume				High Buy Volume				High Sell Volume			
		Average	SD	Max	Min	Average	SD	Max	Min	Average	SD	Max	Min
	Number of stocks per data set	929.8	62.6	1047.0	760.0	943.2	69.5	1081.0	794.0	933.0	67.9	1048.0	744.0
	1 Day Return	-0.03%	3.73%	31.93%	-29.95%	-0.01%	3.70%	31.93%	-29.95%	-0.06%	3.68%	31.93%	-29.95%
	3 Day Return	0.07%	6.07%	118.52%	-43.06%	0.11%	5.99%	118.52%	-45.77%	0.05%	6.04%	118.52%	-48.12%
Unshortable	5 Day Return	0.12%	7.51%	131.78%	-61.65%	0.15%	7.45%	131.78%	-61.65%	0.09%	7.47%	131.78%	-61.65%
	10 Day Return	0.40%	10.91%	514.13%	-63.39%	0.37%	10.72%	514.13%	-63.39%	0.39%	10.86%	514.13%	-63.39%
	20 Day Return	1.06%	16.02%	634.40%	-73.46%	0.97%	15.61%	634.40%	-61.29%	1.07%	16.23%	634.40%	-73.46%
	50 Day Return	2.68%	27.16%	1013.60%	-78.02%	2.55%	26.77%	1013.60%	-78.85%	2.71%	27.02%	1013.60%	-78.02%
	Number of stocks per data set	394.1	32.9	482.0	322.0	396.1	31.7	449.0	318.0	398.9	42.0	525.0	322.0
	1 Day Return	0.06%	2.66%	21.80%	-29.90%	0.08%	2.59%	24.62%	-29.90%	0.05%	2.62%	21.80%	-29.90%
	3 Day Return	0.24%	4.30%	33.85%	-52.86%	0.22%	4.18%	33.85%	-50.49%	0.28%	4.26%	33.04%	-52.86%
Shortable	5 Day Return	0.35%	5.40%	45.30%	-64.60%	0.34%	5.25%	45.30%	-64.60%	0.41%	5.38%	45.30%	-64.60%
	10 Day Return	0.60%	7.31%	81.00%	-63.98%	0.61%	7.24%	81.00%	-63.98%	0.67%	7.32%	81.00%	-63.98%
	20 Day Return	1.17%	10.24%	110.19%	-68.40%	1.14%	10.23%	103.60%	-68.40%	1.26%	10.31%	140.71%	-68.40%
	50 Day Return	1.88%	16.50%	168.59%	-72.40%	1.83%	16.54%	168.59%	-72.40%	2.05%	16.57%	177.06%	-72.40%

5.3.2 Signaling Hypothesis

In this section, we investigated further in the relationship between Standardize unexpected earning using analyst forecast (SUEAF) and stocks in high volume group while controlling the beta, size, short term interaction, midterm inter action and eliminated outlier (data points that provide SUEAF beyond three standard deviations). The results are shown in Table 10 and Table 11. The results show that abnormal high buy volumes really provide the positive surprise while abnormal high sell volumes provide the negative surprise. However, only surprise from stocks that categorized as abnormal high buy volume while not categorized by high sell volume is statistically significant at 95% for n=1 case and 90% for n=8 case, so these results only provide partial support for signaling hypothesis. One of the possible explanations is that firms may want to spread good news to market more than bad news. Another possible explanation is that the amount of analyst researches is small comparing to all of the stock that we test.

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Table 4

Categorized by n=8 criteria. In each type of volume group, we form portfolio one day before announcement date base on type of volume and abnormal degree criteria to see whether abnormal high buy/sell can predict direction of the announcement or not. Positive coefficient mean that group of volume predict positive surprise while negative coefficient mean that group of volume predict negative surprise.

VARIABLES	HB	HS	HBNHS	HSNHB
High Volume	1.257	-3.906	8.941'	-2.334
	(4.440)	(4.211)	(5.959)	(5.253)
beta	-3.870*	-3.953**	-5.778***	-5.426***
	(1.984)	(1.983)	(1.267)	(1.272)
size	2.11e-05**	2.11e-05**	1.91e-05**	1.94e-05**
	(8.50e-06)	(8.50e-06)	(8.30e-06)	(8.31e-06)
mti	8.375***	8.363***	8.293***	8.291***
	(1.580)	(1.580)	(1.576)	(1.577)
sti	9.676***	9.595***	9.616***	9.602***
	(1.428)	(1.428)	(1.426)	(1.427)
Observations	3,419	3,419	3,419	3,419
Adj-R2	0.0231	0.0229	0.0237	0.0231

Standard error in parenthesis
The *** symbol next to each variable are indicate significant coefficients at 1% of two-sided test.
The ** symbol next to each variable are indicate significant coefficients at 5% of two-sided test.
The * symbol next to each variable are indicate significant coefficients at 10% of two-sided test.
The ‘’’ symbol next to each variable are indicate significant coefficients at 1% of one-sided test.
The ‘’ symbol next to each variable are indicate significant coefficients at 5% of one-sided test.
The ‘ symbol next to each variable are indicate significant coefficients at 10% of one-sided test.

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Table 5
Categorized by n=1 criteria. In each type of volume group, we form portfolio one day before announcement date base on type of volume and abnormal degree criteria to see whether abnormal high buy/sell can predict direction of the announcement or not. Positive coefficient mean that group of volume predict positive surprise while negative coefficient mean that group of volume predict negative surprise.

VARIABLES	HB	HS	HBNHS	HSNHB
High Volume	2.664	-0.503	8.196''	1.071
	(4.510)	(4.332)	(6.246)	(5.556)
beta	-3.758*	-3.908**	-5.718***	-5.555***
	(1.984)	(1.983)	(1.265)	(1.271)
size	2.12e-05**	2.12e-05**	1.91e-05**	1.93e-05**
	(8.50e-06)	(8.50e-06)	(8.31e-06)	(8.31e-06)
mti	8.339***	8.369***	8.296***	8.263***
	(1.579)	(1.581)	(1.577)	(1.578)
sti	9.700***	9.657***	9.618***	9.613***
	(1.427)	(1.428)	(1.426)	(1.427)
Observations	3,419	3,419	3,419	3,419
Adj-R2	0.0231	0.0229	0.0237	0.0231

Standard error in parenthesis
The *** symbol next to each variable are indicate significant coefficients at 1% of two-sided test.
The ** symbol next to each variable are indicate significant coefficients at 5% of two-sided test.
The * symbol next to each variable are indicate significant coefficients at 10% of two-sided test.
The ‘’’ symbol next to each variable are indicate significant coefficients at 1% of one-sided test.
The ‘’ symbol next to each variable are indicate significant coefficients at 5% of one-sided test.
The ‘ symbol next to each variable are indicate significant coefficients at 10% of one-sided test.

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CHAPTER 6

CONCLUSION

This paper shows that giving each stock an equal weight, even though the stocks that experience abnormal total trading volume cannot predict future return, the stocks that experience abnormal buy (sell) trading volumes compare to their normally buy (sell) trading volumes can predict and contain information about one-day future returns. Stocks with abnormally high buy volumes tend to be followed by positive returns while stocks with abnormally high sell volumes tend to be followed by negative returns. The results are controlled with beta, size and past price movement.

Researches in the past found that one of the explanations of predictability of abnormal trading event is visibility hypothesis. Stocks with abnormal high trading volumes tend to catch investor attention, which leads to positive return prediction. However, our research finds that this hypothesis is not consistent with our finding. We found no significant result that abnormal high total, buy or sell trading volumes can catch investor attention.

Another explanation of predictability is the signaling hypothesis. We find that a stock that has abnormal high buy volume before earning announcement can predict positive earnings surprise. However, we find no evidence that abnormal high sell volume can predict negative earnings surprise. Our result also suggests that there might be others explanation behind predictability of abnormal trading volumes event that we have not discovered yet which we will leave it to future study.

Finally, this finding should benefit investors who invest in the Thai stock market to make a superior return. Our results suggest that investors should take a long position on abnormal high buy volume stock while they should take a short position on abnormal high sell volume stock as long as their transaction fee is less than 0.17%.

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