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TESTING THE EFFECT OF INVESTOR ATTENTION ON STOCK MARKET RETURN AND VOLATILITY: EVIDENCE IN VIETNAM STOCK MARKET

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TABLE OF CONTENTS

LIST OF TABLES

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ABSTRACT

This study investigates the relationship between investors' attention, which is measured by Google search volume index, and the index performance (index return and volatility) in Vietnamese stock market. I will test the role of attention in predicting market performance. Moreover, past return will be considered when measuring the impact of investors' attention on future return and volatility

The data is obtained weekly from December, 2006 to November, 2014. Stock indices are Vnindex and Hastc. Google Search Volume Index (SVI) is used as a measure for investors' attention. Granger causality test, VAR estimations and OLS method are applied in this study in order to test whether investors' attention is useful in predicting future stock performance and the sign of this effect as well as how the effect of investor attention is affected by changes in the past return.

Results show that both index return and volatility of Vnindex are fairly quickly influenced by search volume. This impact is not influenced by the sign of past return as well as the past return. In case of Hastc, there exists a delay in the impact of past search volume on the index return. Moreover, this impact will increase conditional on a unit change in the past return of Hastc. In the opposite direction, the results also suggest that search volume index is also affected by index return and volatility.

KEYWORDS: search volume index, investor attention, index return, index volatility, market efficiency.

1. INTRODUCTION

As human being, we face with the issue of limited cognitive resources. According to Kahneman (1973), attention is a scare cognitive resource. In the massive amount of information available, people are only able to pay attention to the information that get their attention and ignore the others due to the limitation in the cognitive-processing capacity of human brain.

To specify, in financial market, Barber & Odean (2008) stated that when searching information about the stock that investors want to buy, they face with the difficulty that there are thousands of stocks in the market, which limit the capacity to process information of investors. They might pay more attention on some stocks and ignore other stocks. As a result, they are likely to buy stocks that have first caught their attention even they are not stocks that have the best performance in the stock market.

In addition, the vast amount of online information and services may lead investors to become overconfident in their ability to choose stocks, leading to an irrational trading decision of investors in the financial stock market (Barber & Odean 2001A). Consequently, these irrational investors might drive the market return and volatility and push the stock price further their fundamental values. Many researches have provided evidence for the relationship between irrational investor and stock market return and volatility. (Verma & Verma, 2007, Foucault et al., 2011, Da et al., 2011a, 2011b)

Google Search Volume Index is now considered as a good proxy for investors' attention. In the financial market, professional investors tend to use data gathered on Bloomberg or other data base to predict and trading, but retail investors do not. They tend to use internet via Google to search for information. If they pay attention to something, they will search information about that thing on Internet. As a results, search volume index (SVI) derived from Google Trend is a good proxy for investors' attention. (Da et al., 2011b). Many researchers are successfully using SVI to measure retail investors' attention in their studies such as Bank et al. (2011), Vlastakis & Markellos (2012).

The relationship between investors' attention and stock market performance has been observed recently. Da et al. (2011b) first propose the use of SVI as direct measure for investor attention. They examine the effect of SVI on the stock price through the case of IPO stocks. Their results show that a growth in Search Volume Index can predict higher stock prices in the next two weeks. Furthermore, the relationship between investors' attention and stock market volatility is observed by Aouadi et al. (2013). Their research was conducted in the French stock market. They find that Google Search Volume has significant effect on the stock market volatility even controlling for other determinants of stock volatility. Using indexes as search terms, Vozlyublennaia (2014) also observed the impact of Google search probability on index performance. Results show that investors' attention has significant impact on index return and volatility but the impact last in short term. The past return affects the impact of attention on the future return and volatility. Moreover, the increasing of investors' attention will lead to the decrease in predictability of returns.

Based on the work of Vozlyublennaia (2014), this study is also conducted to find the relationship between investors' attention and Vietnamese stock market return and volatility. The role of attention in predicting market performance is examined and past return will be considered when measuring the impact of investors' attention on future return and volatility. Three hypothesis are tested following Vozlyublennaia (2014). The first hypothesis which is tested in this study can be written as follow

H1: Investors' attention which measured by SVI is useful in forecasting index return and volatility.

This hypothesis indicates that the past value of search volume index can be used to predict future market return and market volatility. If the use of SVI can help forecasting stock market performance, the next issue is that if the effect can last for long time. Thus, the second hypothesis is proposed as

H2: Investors' attention has contemporaneous impact on index return and volatility.

Besides, there are evidences that past returns will have impact on investors' attention, then in turns, attention will affect future return. In this study, this effect will be test also with the third hypothesis:

H3: The increase or decrease on impact of attention depends on the past return.

1.1. Intended contribution

Many previous researches have been conducted to investigate this relationship in developed countries such as French (Aouadi et al., 2013), the United State (Vozlyublennaia, 2014), etc. However, little attention is paid to developing country with undeveloped financial stock market like Vietnam. The contribution of this study is to provide the evidence of this relationship between investors' attention and stock market return and volatility in Vietnamese Stock Market. It helps drawing a comprehensive picture of this relationship in both developed and developing countries. The study's results can be very helpful for investors in forming the more accuracy model to predict future volatility of stock by taking into consideration the impact of individual investors' attention.

1.2. Structure of the study

After the introduction part, the remainder of the thesis is divided into chapter. Chapter 2 provides the literature review of previous studies related to investors' attention as well as the effect of investors' attention on stock market performance. In the next chapter, Chapter 3, the theory of market efficiency, investors' attention and stock market performance (return and volatility) are proposed. Chapter 4 will present the overall view of the data and method which is used in testing the effect of investors' attention on stock index performance. Chapter 5 provides data descriptive statistics as well as econometric analysis results. Finally, conclusion is shown in Chapter 6.

2. LITERATURE REVIEW

Internet is playing a more and more important role in all sides of people life from education, economics, culture and medical. Recently, in financial market, there is a trend among investors to use internet to seek for information that they need to make decision, especially individual investors. Barber & Odean (2001A) found that with the emerging of online brokerage firms and the availability of data on Internet, investors have more accesses and tools to approach information and make decision. Furthermore, some other researchers also study the Internet using habit of investors such as Antweiler & Frank (2004), Rubin & Rubin (2010). However, the vast amount of online information and services may lead investors to become overconfident in their ability to choose stocks and make them to become irrational investors (Barber & Odean 2001A).

The effect of individual investors on volatility has been investigated in many researches. For instant, Verma, R. & Verma, P. (2007) found a significant effect of irrational sentiment on volatility, i.e. investor error is a significant determinant of stock volatility. It is also shown in the research of Foucault et al. (2011) that retail trading has positive impact on the volatility of stock returns and individual investors behave as noise traders. They find that retail investors trade for non-information reasons.

According to Barber & Odean (2008), facing with thousands or more than that of common stocks to choose when trading in the financial market, investors as human beings are unable to rank that huge amount of stocks because of the cognitive and temporal bounds to how much information we can process. Instead of choosing among thousands of stocks, it is easier for them to manage the problem by constraining their choice set (Odean, 1999). Interestingly, stocks that have recently caught their attention will be chosen. However, only individual investors are likely to be net buyers on high attention days and attention affect their buying behavior more than selling behavior. In contrast, the buying behavior of professionals is least influenced by attention and the search set for buy and sell of these investors is the same. Barber & Odean (2008) proposed two reasons for differences between individual investors and institutions, i.e. professional investors such as hedge funds. Firstly, institutions face more choices than individuals when selling their stocks due to their routine sell-short activities and larger amount of stocks they own than most individuals. Secondly, attention si a scare resource for individuals, not for institutions.

Furthermore, according to Da et al. (2011), retail investors are likely to buy stocks that get their attention especially in the event of IPOs. An increase in investors' attention will result in the price pressure and affect volatility. Interestingly, the effect of investors' attention is proved through the China-name stocks effect (Bae & Wang, 2012). It is shown that during the China market boom in 2007, the China-name stocks, i.e. the Chinese companies that have the word "China" included in their company name, appeared to significantly outperform the non-China-name stocks. Bae & Wang (2012) found that both the differences in risk and firm size between China-name stocks and non-China-name stocks cannot explain this outperformance. However, their results shown that the temporary price pressure caused by an increase in investors' attention on China-name stocks is the reason for the drive up in stock price of China-name companies. Four measures of investor attention including news coverage, abnormal turnover, extreme past return and the Google search volume frequency are considered in this study.

In the market, professional investors tend to use data gathered on Bloomberg or other data base to predict and trading, but retail investors do not. They tend to use internet via Google to search for information. If they pay attention to something, they will search information about that thing on Internet. As a results, search volume index (SVI) derived from Google Trend is a good proxy for investors' attention. (Da et al., 2011). Many researchers are successfully using SVI to measure retail investors' attention in their studies such as Bank et al. (2011), and Vlastakis & Markellos (2012). Connecting the issue that Search Volume Index reflects the noise trader behavior in accordance with the "noise trader" model of DeLong et al. (1990), one question is raised whether SVI which is proxy for investor attention can predict the stock market volatility.

Da et al. (2011b) first propose the use of SVI as direct measure for investor attention. They examine the effect of SVI on the stock price, especially the case of IPO stocks.

They suggest that a growth in Search Volume Index can forecast higher stock prices in the next two week. Furthermore, SVI is related to IPO first - day returns. They also find that during the IPO week, the IPO stocks are getting more attention of investors which can be proved by the increase in SVI. The IPO stocks that get higher attention will outperform stocks that get lower attention.

The relationship between investor attention and stock market volatility is observed in the research of Aouadi et al. (2013). Their research was conducted in the French stock market. The results show that Google Search Volume has significant effect on the stock market volatility even controlling for other determinants of stock volatility. In addition, they investigate the different of the effect of two kinds of Google search volume (GSV), i.e. stock-specific GSV and market-related GSV. Stock-specific GSV is obtained by using firm name as the search terms while market-related GSV reflects market-related investor attention by using market index as search term. The results show that the effect of market-related investor attention is stronger than that of the stock-specific attention.

Using indexes as search terms, Vozlyublennaia (2014) also observed the impact of Google search probability on index performance. Researcher found that investors are not likely to use stock ticker symbol to search information on Internet but they might concentrate on broad stock market. As a result, she conducted her study using index data. The research results show that investors’ attention has significant impact on index return and volatility but the impact last in short term. The past return affects the impact of attention on the future return and volatility. Moreover, the increasing of investors’ attention will lead to the decrease in predictability of returns.

In line with these existent researches, this study also examines the effect of investors’ attention on index return and volatility in Vietnamese stock market. Vietnamese stock market is chosen to conduct the research because this emerging market has just established for fourteen years and individual investors still play an important role in the market. Individual investors account for nearly half of all traders in the market and they have enough power to drive the market. Thus, the Google search index which measures the individual attention might have effect on Vietnamese stock market return and can predict market volatility.

Previous studies provide evidence that investors' attention can affect and predict stock market returns and volatility. However, little research attention pay to the small and emerging countries like Vietnam. Thus, in this study, I will test the ability of investors' attention in predicting return and volatility in Vietnamese stock market.

3. THEORETICAL PART

In this chapter, I will focus on main theories including investors' attention, the market performance, i.e. volatility, the market efficiency and behavioral finance.

3.1. Investors' attention

3.1.1. What is attention?

According to Anderson (2004), attention is defined as following:

"Attention is the behavioral and cognitive process of selectively concentrating on one aspect of the environment while ignoring other things. Attention has also been referred to as the allocation of limited processing resources."

In 1953, Cherry first introduced the phenomenon of attention, i.e. cocktail party effect. It is shown that partygoers are able to concentrate on one conservation in a noisy room and do not notice the surrounding noise but still easily notice their name from other ignored conservations. Through Cherry's attention experiment, he found that people can detect their name from the unattended ear which was not shadowing.

Many researches are conducted to give the explanation for this effect. Treisman (1969) proposes the selective aspect of attention by developing the attenuation model. He suggests that brain can easily recognize words that have a low threshold value like someone's name. Selection attention is also studied by many other researchers such as Deutsch & Deutsch (1963), Norman (1968), etc. In 1973, attention was also described by Kahneman but in terms of capacity instead of selection like previous studies. According to him, attention is a scare cognitive resource. In the massive amount of information available, people are only able to pay attention to the information that get their attention and ignore the others due to the limitation in the cognitive-processing capacity of human brain. As a results, attention remains a major area of investigation within many fields such as education, psychology and economic.

3.1.2. Investor attention in financial market

A numerous amount of studies related to the investor attention in financial market has been conducted by many researchers recently. Barber & Odean (2008) are the early researchers who did study on investors' attention. They stated that when searching information about the stock that investors want to buy, they face with the difficulty that there are thousands of stocks in the market, which limit the capacity to process information of investors. They might pay more attention on some stocks and ignore other stocks. As the result, they are likely to buy stocks that have first caught their attention even they are not stocks that have the best performance in the stock market.

Following that, Shane & Jay (2008) also do research in limited attention of investor in securities trading. They found that limited attention has an important effect on liquidity provision in security market. Besides, the effects of investor inattention on stock price dynamics have been studied for many years. (Huberman & Regev, 2001, Hou & Moskowitz, 2005, Cohen & Frazzini, 2008, Hirshleifer, Lim & Teoh, 2009, etc.) In addition, investor attention has an impact on the stock market volatility. Aouadi et al. (2013) show that investor attention is significantly correlated to stock illiquidity and volatility.

Peng & Xiong (2006) investigated the role of investors' attention in category-learning behavior, which is the tendency of investors to process more market and sector-wide information than the firm-specific information. Their results show that limited attention creates an endogenous structure of information. In some cases, investors even allocate all their attention to market and wide information and ignore all firm-specific data. This can be an explanation for the significant increase in abnormal returns of firms who changed to dot.com names without changes in fundamental strategies during the Internet bubble period (Cooper et al., 2001).

Motivated by limited investor attention and anchoring, Li & Yu (2012) highlight the role of Dow 52-week high anchor and the Dow historical high anchor in predicting future returns. Limited attention investors tend to pay more attention to market and wide information than the firm-specific data (Peng & Xiong, 2006). Moreover, Dow index reflects wide market information. Therefore, investors are likely to use Dow index when evaluating market information and making investment decision. As a result, both Dow 52-week high and Dow historical high should be able to forecast future returns.

Based on attention allocation, a financial model of asset prices, in which investors can collect information about combinations of assets, was proposed by Mondria (2010). Due to the information capacity constraints and the restriction in collecting individual assets' information but available information about combinations of assets, investors tend to process signal of a linear combination of asset payoffs and use it as a private signal. Therefore, change in one asset price can have effect in other asset price, leading to asset price co-movement even the two assets are uncorrelated.

Assuming that investors have limited attention and processing power, Hirshleifer & Teoh (2003) found the impact of different information presentation on market price and also offer a new approach of choosing firms among different means of presenting information. Ordinarily, it is stated that investors are rational and all information in the financial market are fully reflected in the stock price. Therefore, the effect of the choice between recognition and disclosure, and between alternative forms of disclosure is identical for investors. However, due to the limited attention, the information that is only implied in the public information set, i.e. less salient information, is likely to be neglected by investors, while salient information is getting more attention. Interestingly, Hirshleifer & Teoh (2003) found that *pro forma* earning disclosure, which can exclude anything that a company believes obscures the accuracy of its financial view, increases investors' perceptions. In terms of aggregation in financial reporting, they see a diversified firm being under valuated during the high foreseen general earnings growth. One explanation is that investors focusing on the recent growth rate of aggregate earnings are likely to overweight low growth segments.

The role of investors' attention is also examined in the FX market using the search volume index. Goddard et al. (2015) find a positive and significant association between investors' attention and volatility of seven currencies pairs' foreign exchange rates.

Moreover, investors' attention is able to forecast the future volatility of the currency returns and becomes a priced risk factor in forex market.

3.1.3. Measure of investor attention

When doing researches in investor attention, one challenge is that what the direct measure for attention is. Many earlier studies have been proposed some indirect proxies for investor attention.

In 2004, advertising expenditures are offered as a measurement of attention in stock market by Grullon et al. (2004). They found that if the expenditures for product market advertising of a firm increase, the number of investors will also increase, which leads to better liquidity of that stock in the market. Similarly, Chemmanur &Yan (2009) also conducted study the impact of advertising on stock return. They state that advertising can help companies attract more investor attention, which in turn lead to a higher contemporary stock return.

Barber & Odean (2008) used three proxies, i.e. whether firms appeared in that day‘s news, stock one day extreme return and stock abnormal daily trading volume to measure the investor attention. They argued that if many investors pay attention to a firm or news about a firm reaches many investors, trading volume of firm's stock is likely to be greater than usual. As a result, firm trading volume can be used as proxy for investors' attention. There can be the case that news which is irrelevant to the firm's future earning possibly cannot affect rational investors and they will not trade, which leads to the trading volume remain unchanged. Moreover, trading volume can be affected by liquidity and trades of some larger investors. However, normally, significant news can have impacts on investors' beliefs, leading to an increase in trading volume and a stronger results are seen in the case of large capitalization stocks which trading volume is unlikely to be affected by a few large investors. The trading volume was also taken into consideration in examining the effect of investors' attention by Gervais et al. (2001), Hou et al. (2008). Besides, the significant movement of a stock price can attract attention of investors even the extreme returns are not related to firm specific information (Barber & Odean, 2008). They state that whatever caused the big movement in stock price, even it is responding to private and non-public information, it is able to attract investors' attention.

The impact of news on investor attention is also suggested in articles of other researchers such as Dellavigna & Pollet (2009), Fang & Peress (2009). Dellavigna & Pollet (2009) examine the difference between effects of Friday announcements with other weekday announcements. Normally, on Friday, investors are distracted from work related activities and they are likely to underestimate the Friday earning announcement. Their results show an 8% lower trading volume around Friday announcements compared to non-Friday announcements caused by limited attention. In the same year, Fang & Peress (2009) investigate the relationship between media coverage of stocks with the performance of mutual funds. They propose mass media coverage as a good proxy for the amount of attention investors pay to an event. Through media reporting, investors can pay more attention with some certain stocks featured in the media and tend to put them into their portfolio. Their findings show that stocks that receive more media coverage are likely to be bought more by mutual funds with size and other stocks' characteristics being controlled. However, the sell activities of funds are not significantly affected by media. Another result indicates the underperformance of mutual funds that display a high tendency to buy media stocks. These evidences also support the limited attention hypothesis.

Price limit events which are suggested by Seasholes & Wu (2007) are the measure of attention. In their research, they choose to study the effect of one attention-grabbing event, i.e. upper price limit events. The results show that a higher number of a given stock is traded by investors who have not used it before after this event than during a usual trading day.

Recently, one direct measure that is considered to be the best proxy for investor attention are proposed by many empiricist, i.e. Search Volume Index (SVI) that can be obtained from webpage http://www.google.com/trends/. Google Trend is a public web-service of Google. It helps user compare the results of searching all over the world from the year of 2004. Trends will perform the data in the form of graphs over time so that we know the level of attentiveness toward a search terms. This chart is very useful when you are researching on the popularity of a particular problem because you can put the data into context of a certain time, which makes the information obtained will be more meaningful. Figures on the graphs are normalized and ranged from 0 to 100. They reflect how many searches have been done for a search term relative to the total number of searches done on Google over time. They are not the absolute amount of searches at that time. Because the numbers on the graph are normalized, a decrease in this number does not mean that the search volume related to that search term decrease. It can be indicated that the popularity of that search term is decrease, which mean that people are not searching that term as much as before. For example, as can be seen in Figure 1, the Search Volume Index with the search term "vnindex" experienced a soar in 2007 – 2008, followed by a slightly decrease in the following years. The highest point in the graph has the index equal to 100 in 2007, which means that at that time the key word "vnindex" are search most popularly. In the next years, this search term is less popular than the year 2007, so the index is around 60, 50 (equal to 60%, 50% compare to the period 2007-2008).

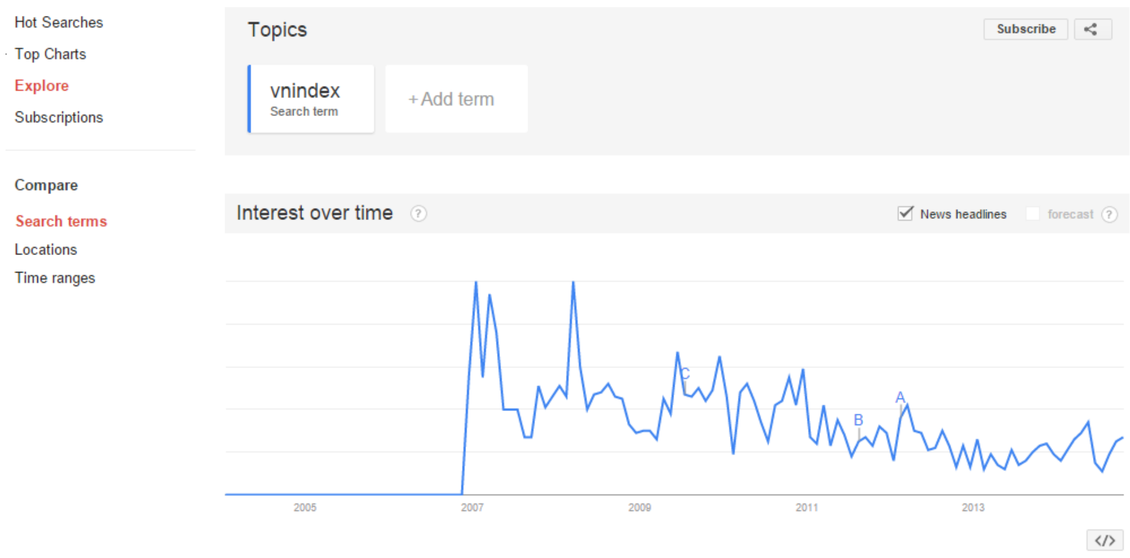


Figure 1. Example of graph on Google Trends. Search term: "vnindex"

3.2. Volatility

3.2.1. Volatility and properties of volatility

Volatility are getting more and more attention of investors because of its value in risk management, option pricing, asset allocation, hedging. In economics, volatility is defined as the rate of change in the price over a period of time. Generally, volatility can be interpreted as the standard deviation σ or variance σ^2 which measures the amount of dispersion from the average. If the standard deviation of stock price is low, it means that the price of stock is quite close to the mean value, i.e. expected value. In contrast, high standard deviation means that the price of stock is spread out over a large ranges of values. In terms of mathematics, the annualized volatility is calculated as the standard deviation of the annual logarithmic return of asset $\sigma_T = \sigma\sqrt{T}$. Where σ_T is the generalized volatility, T is the time horizon.

In finance, there are some volatility terminologies used such as historical volatility, realized volatility, implied volatility, etc. Historical volatility reflects the past price change of financial instrument. Historical volatility is also referred as realized volatility of assets. In contrast, implied volatility reflects the investor's expectation of the future volatility, which can be derived from the Black-Scholes formula.

The properties of stock market volatility are observed by a larger amount of literature for many years. The first characteristic of stock return volatility is the asymmetric responses of volatility which is also known as leverage effect. The positive return and negative return do not have the same effect on volatility. Positive returns have a smaller impact on future volatility than do negative returns of the same absolute amount. (Braun et al 1995, Engle & Patton 2001, Andersen et al. 2001). The second one is volatility clustering which describes the tendency of large changes in asset prices to follow large changes and small changes to follow small changes (Bentes et al. 2008). Otherwise, mean reversion (volatility will return to its mean value), long memory which reflects long run dependencies between stock market returns and volatility, and fat tail distribution are also reported as properties of volatility. (Engle & Patton 2001, Poon 2005, Fama 1965).

3.2.2. Volatility forecasting

Volatility has an important role in risk management, option pricing and portfolio hedging. However, in order to calculate the option price or form a hedging strategy, the future volatility is required. As a results, forming model to estimate future value of volatility is getting attention of investors in the financial market. Numerous models are conducted to estimate volatility such as simple historical model consisting random walk, historical mean, moving average; ARCH family model, i.e. EGARCH, IGARCH, GJR-GARCH, etc.; RiskMetrics EWMA model. Due to the simplicities of simple historical model, they fail to explain some properties of volatility process. GARCH family models and EWMA model are used more popularly in the market. Besides, the volatility estimates are influenced by economic news (Engle & Ng 1993), investor sentiment (Da et al. 2010), expected market risk premium (French et al. 1987), etc.

Table 1. Formula summary of some volatility forecasting model

Model	Formula
RiskMetrics EWMA	$\sigma^2_{t\|t-1} = (1-\lambda)\sum_{i=0}^{\infty}\lambda^i r^2_{t-i} = (1-\lambda){r_{t-1}}^2 + \lambda\sigma^2_{t-1\|t-2}$
GARCH	$\sigma^2_t = \omega + \sum_{j=1}^{p}\beta_j\sigma^2_{t-j} + \sum_{i=1}^{q}\alpha_i u^2_{t-i}$
EGARCH	$\ln(\sigma^2_t) = \omega + \sum_{i=1}^{q}[\alpha_i z_{t-i} + \gamma_i(\|z_{t-i}\| - E(\|z_{t-i}\|))] + \sum_{j=1}^{p}\beta_j \ln(\sigma^2_{t-j})$
GJR-GARCH	$\sigma^2_t = \omega + \sum_{i=1}^{q}[\alpha_i + \lambda I(u_{t-i} < 0)]u^2_{t-i} + \sum_{j=1}^{p}\beta_j\sigma^2_{t-j}$
I-GARCH	$\sigma^2_t = \omega + u^2_{t-1} + \sum_{i=2}^{q}\alpha_i\,(u^2_{t-i} - u^2_{t-1}) + \sum_{j=1}^{p}\beta_j(\sigma^2_{t-j} - u^2_{t-1})$
FI-GARCH	$\sigma^2_t = \omega[1-\beta(L)]^{-1} + \{1 - [1-\beta(L)]^{-1}(1-\alpha(L)-\beta(L))(1-L)^d\}\ u^2_t$ $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \alpha_3 L^3 + \cdots + \alpha_q L^q$

	$\beta(L) = \beta_1 L + \beta_2 L^2 + \beta_3 L^3 + \cdots + \beta_p L^p$
APARCH	$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i [\lvert u_{t-i} \rvert - \gamma_i u_{t-i}]^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta$

The issue of the effective of each model in forecasting volatility is controversial. Cumby et al. (1993) find that the explanatory power of historical volatility model is equal GARCH model while GARCH models seem to be more complicated. On the other hand, in many other studies, GARCH type model are proposed to be the most accurate volatility forecast models (Andersen & Bollerslev 1998, McMillan & Speight 2004). Besides, some researchers conclude that there are no model that outperforms all other in all markets. The forecast results depends on the choice of error statistic and the market they use to observe. (Brailsford & Faff, 1996, McMillan & Kambouroudis, 2009).

3.3. Market efficiency

3.3.1. Definition

An efficient financial market was defined by Fama (1970) as the market “in which prices always “fully reflect” all available information”. Fama (1970) also stated three sufficient conditions for financial market efficiency, i.e. no transaction costs in trading securities, freely available information to all market participants and agreement of all investors on the implications of given information and distribution of future prices of securities. These conditions are sufficient for market efficiency but are not necessary.

3.3.2. Market efficiency levels

Fama (1970) identified three levels of market efficiency, i.e. weak-form, semi-strong form and strong- form efficiency.

(i) Weak-form efficiency

In a weak-form efficient financial market, all available information of the past prices is fully reflected in the current prices of securities (Fama, 1970). As a result, past prices are useless in predicting future prices. Simply, in this kind of market, the buy and hold strategy is preferred. Technical analysis method has no use in this kind of efficient market. Technical analysts or chartists study the records of past prices to exploit price patterns that provide them profits if stock price response slowly enough to changes in fundamental factors. However, in weak-form efficient market, all past stock prices are available and costless to all investors. If there is a buy signal, a mass of investors will try to exploit it, which results in an immediate price increase and the signal loses its value. (Bodie et al. 2014:354)

(ii) Semi-strong efficiency

In semi-strong efficient financial market, all public information regarding the prospects of a firm is fully reflected in asset prices. The public information is included the available information of the past prices, past trading volume and other public information such as earning announcement, IPO events, quality of management, accounting practices. Asset prices adjust to new public information very quickly, which means that there will be no abnormal returns by trading on that public new information. In this case, neither technical analysis nor fundamental analysis has any usefulness in investors' trading strategy. (Bodie et al. 2014:354).

(iii) Strong-form efficiency

In strong-form efficiency, stock prices reflect all public and private information related to the firm. Even company insiders cannot earn excess return. However, this level of market efficiency is still on debate. Since, corporate officers, directors, substantial owners, their relatives and associates might have inside information in advance. They still have enough time to make profit before inside information being published. There exists a law, i.e. rule 10b-5 of the Security Exchange Act of 1934, which limits insider trading. However, preventing insider trading is not that easy. (Bodie et al. 2014:354)

3.3.3. The efficient market hypothesis

Efficient market hypothesis (EMH) states that "stocks already reflect all available information" (Bodie et al. 2014:351). According to the efficient market hypothesis, stocks are traded at their fair value on the stock exchange market. As a result, it is impossible for investors to outperform the overall market or "beat the market" by purchasing undervalued stocks.

There are three versions of Efficient Market Hypothesis: the weak, semi-strong and strong forms of the hypothesis. The weak form hypothesis states that stock prices already reflect all historical information such as the history of past prices, trading volume, or short interest (Bodie et al. 2014:353). This form of EMH can be tested by measuring the serial correlation of stock market returns. A positive serial correlation indicates that a positive return tends to be followed by a positive return and vice versa, a negative serial correlation means a negative return following a positive return. The semi-strong form hypothesis says that stock prices already reflect all public available information. Some market anomalies such as the small-firm-in-January effect, the neglected-firm effect, liquidity effect, book-to-market ratios and post-earning-announcement price drift are utilized to examine semi-strong form of EMH. Based on fundamental analysis, if one can earn abnormal returns, the semi-strong hypothesis is violated. Finally, the strong form hypothesis states that stock prices already reflect all available public and inside information. This strong form hypothesis will be rejected if it is proved that insiders can make superior profits in their firm's stock trading using their privileged information of the firm's stock. (Bodie et al. 2014:354).

3.4. Behavioral finance

3.4.1. Definition

Behavioral finance is a new field of finance which provides explanation for most financial phenomena using models in which some agents are not fully rational. There are two “pillar” of behavioral finance, i.e. limit to arbitrage and psychology. (Kihn, 2011:10)

According to conventional or modern finance, most financial models are based on some assumptions. Firstly, most participants in the financial market are assumed to be rational and predictably in most financial models such as the capital asset pricing model (CAPM). Secondly, in some cases that there are some irrational traders, it is stated that their trades are random and can be canceled each other out without any effect on asset price or rational arbitrageurs in the market can help eliminate these influences on prices. (Kihn, 2011:28-29). However, there is little empirical reason to believe that irrational traders cancel each other out. In some case, they even can push the asset price further away from their fundamental value. In terms of rational arbitrageurs helping push the price back to the true value, it seem to face some matter in the actual financial market. There appear limits to arbitrage that arbitrageurs are likely to face with when trading such as transaction costs, capital constraint, liquidity constraints and other behavioral limits to arbitrage. (Kihn, 2011: 30). As time flies, there appear some anomalies that conventional financial theories fail to explain but could be explain by behavioral finance. Thus, behavioral finance become more and more important in the financial world although still some supporters of efficient market are critics of behavioral finance.

3.4.2. First “pillar” of behavioral finance: The Limits to Arbitrage theory

As mentioned above, with the participation of both irrational and rational traders in the efficient financial market, there should be no arbitrage opportunity. If the asset prices are mispriced by the irrational traders, the rational investors will help correcting the value by trading this mispriced asset through arbitraging. It is stated that arbitrage opportunity is riskless and will quickly disappear. However, there come some evidences showing that arbitrage opportunities do not quickly disappear even investors know how to exploit them. The limit to arbitrage theory will give the explanation for this phenomenon.

The limit to arbitrage is one of the two block buildings of behavioral finance. It is stated that arbitrage is limited, risky and costly. Let see an example. After carefully analyzing, you see that the fundamental value of stock A is relatively lower than stock B which can be considered as a substitute for stock A. So you decide to arbitrage by going long stock A and short stock B. However, you may consider some risks, i.e. currency, timing, short sales constraints, cost and idiosyncratic risk. Firstly, company A and B are in two different countries with two currencies. In order to eliminate the currency risk, you have to go long and short currency A and B also. But the hard thing is that how can you calculate the amount of money you should trade when one or both countries are likely to change their currency during your trading. Secondly, in order to arbitrage, you need to trade the two stocks at the same time with the same amount. But you cannot assure that you can by the same amount of stock B after you first go short stock A at exactly same time. Thirdly, you should consider the short sale constraints. To specify, you may see it hard to trade if the government pass a law that against short sales or limits price movements for short sales. Fourthly, the transaction costs should be taken into consideration because costs can change or government can change the tax on short term gains or losses. Finally, you should take account of specific business risks like the different company’s structure and other related risks. Taking into consideration all the costs and risks you may face with, will you continuously do arbitrage? (Kihn, 2011: 65-66)

Three main risks and costs are stated by Kihn (2011:65), i.e. fundamental risk, noise trader risk and implementation risk. Fundamental risk occurs when the bad new information arrives to the market right after you have just purchase the security. Theoretically, it is said that this risk can be eliminated if you purchase a perfect substitute. However, in reality, it is hard to find a perfect substitute security to hedge the fundamental risk. Regarding the noise trader risk, it is introduced by De Long et al. (1990) and by Shleifer & Vishny (1997). Noise trader risk occurs when the pessimistic trader become even more pessimistic about the future, resulting the mispricing being worsen in the short run. Lastly, the implementation cost refer to transaction costs, price impact, short-sale constraints, legal constraints, horizon, information costs, taxes, etc.

There appear some evidences of mispricing and limits to arbitrage.

Firstly, it is the case of twin shares or dual-listed companies. The typical example is the case of Royal Dutch and Shell Transport in 1907. They are two independent companies listed in two different countries, but they agree to operate their business as one company on a 60:40 basis. It means that 60% of the new company is comprised by Royal Dutch and 40% by Shell Transport. Theoretically, share of Royal Dutch must be traded at 1.5 times Shell Transport's share. However, in reality, Royal Dutch has traded 35% underpriced relative to parity and sometimes 15% overpriced. Here comes an arbitrage opportunity for investors since in March 11983, Royal Dutch was traded at a price 10% undervalued. But in fact, the share value of Royal Dutch decrease even further in the following six months. In this case, the two shares are good substitute, the implementation costs are low, but the arbitrage was limited because of noise traders. (Kihn, 2011:69-71)

Secondly, another evidence of limit to arbitrage is "carve-outs". An equity carve-out refer to the Initial Public Offering (IPO) in which the parent company publicly sells a portions of one of its subsidiary companies. According to law of one price, the parent company YZ should be worth equal to or at least very close to the sum of its parts, i.e. YZ = Y + Z. However, this can be applied in the case of the parent 3Com and its subsidiary Palm in 2000 where the sum did not equal to the parts. (Kihn, 2011:72)
Another evidence calls index inclusion where stock price changes when it is added to or drop from an index. Yahoo, for example, jumped further 24% after being added to S&P 500. Here comes an arbitrage opportunity for investors because stock price changes without changing in the fundamental value. Arbitrageurs would be able to push the price to its fundamental value by short a good substitute for the stock being added in the index. However, in fact, the stock price can continue to increase due to noise trader risk. (Kihn, 2011:84-86)

3.4.3. Second "pillar" of behavioral finance: Psychology

Psychology part of behavioral finance is considered as a kind of bonus that accompanies the limit to arbitrage part (Kihn, 2011:93). Relating to the financial market, six errors and bias in human thinking and problem solving are listed including overconfidence, optimism and wishful thinking, representativeness, conservatism, belief perseverance and confirmation bias, anchoring and availability biases.

Overconfidence is determined as a psychological bias in which people overestimate their knowledge, their ability and their future prospects (Barber & Odean, 2001B). People often estimate their ability above the average level. Overconfidence has a significant impact on trading behavior of investors. For example, overconfident investors are likely to trade more than rational investors (Statman et al., 2006), men trade more than women due to their higher overconfidence and men' performance is lower than women (Barber & Odean, 2001B).

Optimism and wishful thinking indicates that people tend to be overly optimistic about positive outcomes and under optimistic about negative outcomes (Kihn, 2011:94). Over optimism is one of evidences of wishful thinking. Over optimism is a tendency that people is biased about the probability of personally relevant events, overestimating the probability of wanted events and underestimating that of unwanted events. To specify, in financial market, investors tend to apply high likelihood for positive outcomes while apply low likelihood for negative outcomes, leading to normatively problematic for investors.

Representativeness is defined by Tversky & Kahneman (1972) as "the degree to which an event is similar in essential characteristics to its parent population, and reflects the salient features of the process by which it is generated". In other words, it can be understood that how alike something is to that which is known (Kihn, 2011:95). Specifically, for example, in financial market, if one investor knows one stock that is outperformed and another stock that seem to be a representative of that outperformed stock, investor tend to apply a higher probability for the representative stock to be outperformed than it really is.

In the case of conservation, if a data sample is old, investors tend to overweight their priors. In other words, conservatism is the reluctance of investors to react to new information, even this information should require a change in one’s strategy.

Belief perseverance occurs when people is persistent to their process and strategies even their strategies are failing, ignoring the new information that contrast to their beliefs. It is stated that to some people, their original evidential bases can be destructed, but the belief cannot be abandoned (Kihn, 2011:95).

Anchoring is a tendency by people to depend too much on one specific information when making decision (Kihn, 2011:96). In the financial world, anchoring can be a reason of investors’ failure if investors make their decision based on irrelevant information. For example, if investors anchor on a high value that one stock achieve recently, they might believe that the decrease in that stock price is due to mispricing. As a result, they will see this is an opportunity to buy stock at a discount. However, in many cases, the reason behind the decrease in value of one stock is changes in company’s underlying fundamentals. If this case occurs, investors will lose their money.

Availability biases is the tendency by people to heavily weigh their decision toward more recent and actual experiences and they make any new opinion biased toward these experiences. For instance, in the case of loser stocks, investors tend to overreact to bad news, driving the stock prices down unreasonably although these losers might be no more dangerous than it has ever been. After a few time, investors might realize that their judgment is not true, the stocks are underpriced and these losers begin rebounding. The opposite is true with the winners.

4. DATA AND METHODOLOGY

This chapter will focus on describing the data and method using in this study. In order to test the relationship between investors' attention and market performance, the method that was used in the research of Vozlyublennaia (2014) is applied using the Granger Causality tests and VAR estimation model. The weekly data is obtained during the period from December, 2006 to November, 2014. In line with previous researches (Aouadi et al., 2013, Vozlyublennaia, 2014, etc.), Search volume index is used as a proxy for investors' attention with the search terms are market indexes, i.e. vnindex and hastc.

4.1. Data

4.1.1. Index return

The weekly return of Vn-index and Hnx-index is obtained during the period from December, 2006 to November, 2014. The price indices can be obtained from the website of Hanoi stock exchange market and Ho Chi Minh stock exchange market and the data base of the University of Vaasa. The data is used here is the weekly data because of some reasons. Firstly, the Vietnamese stock market have just operated since 2000. At the beginning, the stock market only hold three trading days per week on Monday, Wednesday and Friday. Moreover, due to Tet holiday and other holidays per year, the stock exchange will close, which leads to quite a lot missing value for daily stock return. Secondly, the infrequent trading data can badly affect the statistical results, which can be improved by using longer period of time.

Following the method in the study of Phan & Zhou (2014), the weekly return is calculated by taking the natural logarithm of the index Friday closing price minus the natural logarithm of the previous Friday closing price. The Friday closing price is chosen in order to be in line with the data collected from Google Trends.

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

where P_t is the index price at time t, P_{t-1} is the index price at time t – 1.

4.1.2. Standard deviation of index return: proxy for market volatility

Following the work of Aouadi et al. (2013), the weekly standard deviations of index returns are used as a proxy of market volatility. In a developing country like Vietnam, calculating daily volatility based on high frequency data, i.e. intraday data, is quite difficult because the historical intraday data is not available. As a result, weekly standard deviation, which is proxy for market volatility, is measure using daily return of each week from Friday of this week to Friday of the following week.

4.1.3. Search volume index: proxy for investors' attention

Search volume index has been introduced as a new measure of investors' attention recently by Da et al., 2011, Vlastakis & Markellos, 2012, Schmidt, 2012, Mondria et al., 2010, etc. In these studies, the stock ticker symbols are used as the search queries. The results from Google Trends measure investors' attention to that specific stock. However, in this study, I will use the "Vnindex" and "hastc" as the search terms to investigate investor attention instead of a specific stock symbol. The use of indexes as search terms is proposed in the researches of Vozlyublennaia (2014) and Aouadi et al. (2013) also. The reasons why the index is used as search term instead of ticker symbol of a stock are mentioned in the research of Vozlyublennaia (2014). For professional traders, they do not need to search for information on Internet. For individual investors, they are likely to use Google to find information. However, Vozlyublennaia (2014) figure out that individual investors are not likely to search information of individual stock but a broad market index. In addition, facing with a huge amount of stock in the market, individual investors have limitation in processing all information and they need to find information of index to narrow their information and pay attention to the index that performs well. That is the reason why indexes are preferred in this study.

There are two stock trading centers in Vietnam, i.e. Hanoi Stock Trading Center and Ho Chi Minh Stock Trading Center. Vn-Index reflects the fluctuation of stocks listed in Ho Chi Minh Stock Trading Center while HASTC Index reflects the changes of stocks listed in Hanoi Stock Trading Center. The search terms used in this study are “vnindex” for VN-Index and “hastc” for HASTC Index. The search volume index can be obtain by typing these search terms in the search box of Google Trends. The data can be download directly from Google Trends webpage. Besides, I will also check the data by follow the news headlines on the result graph and the location to limit the noise in data.

4.2. Methodology

In this study, in order to test the relationship between investors’ attention and index performance, i.e. index returns and volatility, the Granger Causality tests and VAR estimation model are employed following the method in the research of Vozlyublennaia (2014).

4.2.1. Statistical causality between attention and index performance

Granger causality tests and Vector Autoregression model (VAR model) is used to examine the possibble causality relationships between investor attention and index return and volatility.

Granger Causality tests is used to examine whether investors’ attention is useful in forecasting stock market return. The following model formulas with n lags are applied:

(2) $R_t = c + a_1 SVI_{t-1} + a_2 SVI_{t-2} + \ldots + a_n SVI_{t-n} + b_1 R_{t-1} + b_2 R_{t-2} + \ldots + b_n R_{t-n} + e$

(3) $SVI_t = c + a_1 SVI_{t-1} + a_2 SVI_{t-2} + \ldots + a_n SVI_{t-n} + b_1 R_{t-1} + b_2 R_{t-2} + \ldots + b_n R_{t-n} + e$

where R_t is index returns at time t, SVI_t is the search volume index at time t. If SVI does not Granger Cause R, all coefficients of SVI should equal to 0. If one coefficient of SVI are different from 0, it can be understand that SVI Granger Cause R or SVI is useful in forecasting index return. Thus, F test is applied for the first model to test the null hypothesis H_0: a_1= a_2=…= a_n=0. Similarly, F test is also used for the second model to test if R Granger Cause SVI.

Continuously following the method of Vozlyublennaia (2014), VAR estimation model is employed to determine how quickly SVI affects R. VAR model has the following specification:

$$X_t = a_0 + a_1 X_{t-1} + a_2 X_{t-2} + \ldots + a_n X_{t-n} \quad (4)$$

where X is a vector that include index return and search volume index.
VAR model allows us to test whether one variable has contemporaneous impact on other variables. This model is very useful when using low frequency data.

In order to test the effect of investors' attention on volatility, the same method that is used to examine relationship of attention and index return is applied using Granger Cause test and VAR estimation model.

For the Granger Cause test, the following model is employed with V_t is the index volatility at time t which is measured by standard deviation of daily index return for every week.

$$(5) \quad V_t = c + a_1 SVI_{t-1} + a_2 SVI_{t-2} + \ldots + a_n SVI_{t-n} + b_1 V_{t-1} + b_2 V_{t-2} + \ldots + b_n V_{t-n} + e$$

$$(6) \quad SVI_t = c + a_1 SVI_{t-1} + a_2 SVI_{t-2} + \ldots + a_n SVI_{t-n} + b_1 V_{t-1} + b_2 V_{t-2} + \ldots + b_n V_{t-n} + e$$

In the VAR model, vector X will include index volatility and search volume index.

4.2.2. Investors' attention and the predictability of market return

If the past attention has impact on future return and volatility and in turn, past return and volatility have impact on future attention, it can be interpreted that the impact of attention on index performance depend on the information received by the market (Vozlyublennaia, 2014).

In order to test this hypothesis, these two models will be test following the method of Vozlyublennaia (2014) using OLS method to test the model:

$$(7)\quad R_t = a_1 + \sum_{i=1}^{4} a_t R_{t-i} + \sum_{i=1}^{4} b_t SVI_{t-i} + \sum_{i=1}^{4} \mu_t SVI_{t-i} * D(Rt - 1 < 0) + e_t$$

where R_t is the index return, SVI_t is Google search volume index and D is dummy variable that takes the value of 1 if index return is negative and 0 otherwise. The coefficient μ indicates the change in the coefficient of SVI if lagged index return is negative. In other words, if the past return is negative, the impact of search volume on current return will increase or decrease by the value of μ. If the coefficient μ is significant, the sign of past return, i.e. past return is positive or negative, will affect current index return depending on investors' attention.

Next, the magnitude of investors' attention impact on recent index return is examined whether it is affected by a unit change in past return, not the sign of past return. Following the method of Vozlyublennaia (2014), the model below is tested.

$$(8)\quad R_t = a_1 + \sum_{i=1}^{4} a_t R_{t-i} + \sum_{i=1}^{4} b_t SVI_{t-i} + \sum_{i=1}^{4} \mu_t SVI_{t-i} * R_{t-i} + e_t$$

Where R_t is the index return, SVI_t is Google search volume index. The coefficient μ measures the increase or decrease in the impact of attention conditional on a unit change in the past return. In the opposite direction, this coefficient also measure the change in the impact of past index return on recent return conditional on a unit change in the investor attention.

When testing the effect of investors' attention on volatility conditional on a unit change in the past return, the following model is estimated:

$$(9)\quad V_t = a_1 + \sum_{i=1}^{4} a_t V_{t-i} + \sum_{i=1}^{4} b_t SVI_{t-i} + \sum_{i=1}^{4} \mu_t SVI_{t-i} * R_{t-i} + \sum_{i=1}^{4} \emptyset_t R_{t-i} + e_t$$

where V_t is the index return volatility, SVI_t is Google search volume index and R_t is the index return. The coefficient μ measures the effect of attention on the market volatility conditional on a unit change in the past index return. In other words, with a unit change in the past index return, the impact level of search volume on recent index volatility increase or decrease by μ units.

5. EMPIRICAL PART

Before going to the main parts, i.e. the descriptive statistic and results of Granger causality test and VAR estimation, I will go through some introduction of the Vietnamese stock market.

5.1. Vietnamese stock market

5.1.1. Introduction of the Vietnamese stock market

After a long time for preparation and waiting, in November of 1996, the State Security Commission of Vietnam (SSC) was established. SSC is in charge of developing the country's security market. Being supervised by SSC, two stock trading centers, i.e. the Ho Chi Minh Stock Trading Center (HOSE) and the Hanoi Stock Trading Center (HASTC) were established in 2000 and 2006, respectively. Only big companies that have the capital more than VND 80 billion are listed on the HOSE. The medium and small companies are listed on HASTC. Until now, there are 305 companies listed on HOSE and 368 companies listed on HASTC. So far, 49 fund management companies are activating in the stock market; about 1 million trading account of individual domestic investors and 20,000 trading account of individual foreign investors. Individual investors account for largest portion in the total investors in the Vietnamese stock market.

Table 2. Sector summary in 2014

	Sectors	Number of companies	Market capitalization (VND billion)
1	Real estate	58	156,870
2	Rubber	9	14,872
3	Security	20	35,272
4	Telecommunications	24	15,274
5	Services – Travelling	14	14,649
6	Pharmaceuticals	21	19,090
7	Education	23	1,313
8	Mineral	28	16,069

9	Energy	19	121,270
10	Bank	16	222,693
11	Steel	14	11,288
12	Petroleum	31	113,054
13	Plastics	20	10,011
14	Manufacturing	38	26,713
15	Consumer Foods	28	209,105
16	Trade	21	11,097
17	Aquatic	19	22,265
18	Transport	45	36,438
19	Construction materials	46	20,098
20	Construction	76	42,844

Source: http://www.cophieu68.vn/categorylist.php

Table above shows the summary information of sectors in Vietnamese stock market. As can be seen from the table, bank sector has the biggest market capitalization, following by consumer foods, real estate and energy sectors.

5.1.2. The performance of Vietnamese stock market

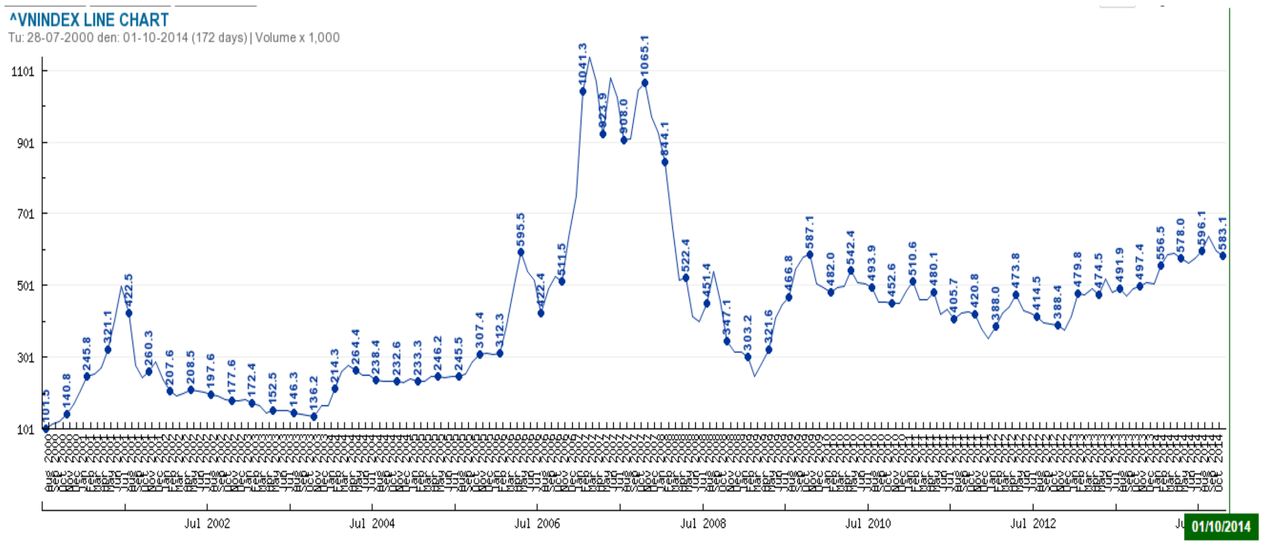


Figure 2. VNINDEX line chart

Source: http://www.cophieu68.vn/snapshot.php?id=^vnindex

Vn-index officially operates from 2000 with the initial point was 100 and reached the peak at 571 points in June of 2001. At that time, the number of companies listed on the stock market is just a few. In the end of the year 2001, Vn-index lost 300 points and close at 235.4 points. In 2006, this is the time for a hot trend called “stock” for investors. Vn-index increased to 600 points in the beginning of April. Many big companies such as Vinamilk published the financial statement with a high profit, which forced investors buy stock in the market. Many individual investors tried to collect all of their money to buy stock at that time. They even were not care about the firm specific information. This trend pushed the price of stock. After that, stock price began to reduce as some investors’ prediction. However, in 2007, Vietnamese stock market experienced a quick recover after Vietnam joined WTO. The year of 2008 is the worst year for stock market when stock price continuously decreased. Investors tried to sell their stock to keep money. Until now, experiencing the decrease and then recover, Vn-index remain at around 500 point and is expected to increase in the future.

5.2. Descriptive statistics

Table 3. Descriptive statistics

Table 3 shows the descriptive statistics of six variables, i.e. weekly return, weekly volatility and weekly search volume index of Vnindex and Hastc during the period from December of 2006 to November of 2014.

	VNINDEX			HASTC		
	Return	Volatility	SVI	Return	Volatility	SVI
Mean	-8.6E-05	0.0136	1.3312	-0.0011	0.0175	0.7877
Median	0.0000	0.0119	1.3802	-0.0004	0.0147	0.7781
Maximum	0.0724	0.0459	1.9823	0.0821	0.072	1.8751
Minimum	-0.0764	0.0010	0.0000	-0.1030	9.E-05	0.0000
Std. Dev.	0.0194	0.0077	0.2663	0.0227	0.0113	0.5484
Skewness	-0.1189	1.0561	-1.2938	-0.0224	1.3358	-0.0862
Kurtosis	5.2817	3.9558	6.6815	5.3741	5.2412	1.6167
Jarque-Bera	8.7495	8.9358	3.3665	9.3739	2.0216	3.2306
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-0.0343	5.4491	5.3115	-0.4299	6.9782	3.1429

Sum Sq. Dev.	0.1498	0.0239	2.8234	0.2058	0.0504	1.1968
Observations	399	399	399	399	399	399

As can be seen in the table, the mean return of both Hastc and Vnindex is quite low with negative returns of -0.0011 and -8.6x10^{-5}, respectively. Highest return of Hastc equals to 8.2% and Vnindex reaches to the maximum value of only 7.2%. Meanwhile, in the market downturn period, Hastc and Vnindex decrease to the minimum value of -10.3% and -7.6%, respectively. The gap between maximum and minimum value of Hastc return is much larger than that of Vnindex.

In terms of return volatility, it is shown that Hastc return volatility is higher than that of Vnindex during the period from 12/2006 to 11/2014. Maximum volatilty of Vnindex stays at 4.59% while the minimum value is just 0.1%. Similarly, the gap between maximum and minimum volatility of Hastc is large. The value ranges from the maximum value of 7.2% to the minimum value of about 0%.

Finally, search volume index of both Vnindex and Hastc have the minimum value of 0 in periods that investors do not pay much attention to these indexes. The mean search volume index of Vnindex is higher than that Hastc, which means that Vnindex is geting more attention than Hastc in Vietnamese stock market.

5.3. Statistical causality between attention and index performance

Granger causality tests and Vector Autoregression model (VAR model) is used to examine the possible causality relationships between investor attention and index return and volatility.

Granger causality test was first introduced by Granger (1969) as a statistical hypothesis test in order to determine whether one time series is useful in forecasting another. In this test, the null hypothesis is stated that X does not Granger cause Y. If p-value is smaller than significant level α, the null hypothesis is rejected. It means that X Granger cause Y or X values provide statistically significant information about future values of Y. Besides, VAR estimation model is applied to determine how quickly investors' attention have effect on index return and volatility.

5.3.1. Granger causality test for index performance and search volume index

First of all, Granger causality test is applied for indexes' performance and investor attention which is measured by search volume index. The tables below reports results of P-value for the null hypothesis that search volume index does not Granger cause indexes' return and volatility and that indexes' return and volatility do not Granger cause search volume index. The 2 (top panel), 4 (middle panel) and 6 (bottom panel) lag specifications are added in the model specification.

Table 4. Pairwise Granger causality test for return and volatility of Vnindex and Google search volume index.

This table reports the p-values for Granger causality test on Google search volume index and Vnindex return and volatility. The data is obtained weekly from December of 2006 to November of 2014. Model specifications include 2 lags, 4 lags and 6 lags.

Lag	Null hypothesis	Prob.
2	SVI vnindex does not Granger Cause Return vnindex	**0.0692**
	Return vnindex does not Granger Cause SVI vnindex	0.5361
	SVI vnindex does not Granger Cause volatility vnindex	**0.0003**
	Volatility vnindex does not Granger Cause SVI vnindex	**0.0021**
4	SVI vnindex does not Granger Cause return vnindex	0.2223
	Return vnindex does not Granger Cause SVI vnindex	0.8693
	SVI vnindex does not Granger Cause volatility vnindex	**0.0306**
	Volatility vnindex does not Granger Cause SVI vnindex	0.3901
6	SVI vnindex does not Granger Cause return vnindex	0.1672
	Return vnindex does not Granger Cause SVI vnindex	0.6467
	SVI vnindex does not Granger Cause volatility vnindex	**0.0933**
	Volatility vnindex does not Granger Cause SVI vnindex	0.8746

Table 4 shows results for pairwise Granger causality test for Vnindex performance and SVI with key word “Vnindex”. Both index return and index volatility are influenced by search volume index. Including 2 lags in the model specification reveals the two way statistical significant relationship between investors’ attention and index volatility. Meanwhile, only index return is affected by search volume index. Search volume index seem not to be influenced by the index return. When 4 lags and 6 lags is added in the model specification, the significance of impact of Google search volume index on index return reduces. It can be explained that the model maybe over-specified in terms of number of lags. Moreover, with Vnindex, which captures only large companies’ stock, investors can process information of these companies fairly quickly thanks to mass media, stock returns, trading volume, etc. As a result, investors can respond to new information of large stocks more quickly compare to that of the small and medium stocks. When investors pay more attention to large stocks due to new information coming out, the stock returns will change quickly thanks to quicker response of investor to large stocks compared to small and medium stocks. This can explain for the results showed in table 4, that is only search volume index of two weeks before is useful in predicting Vnindex return and volatility while the SVI of four or six weeks before have less significant impacts. In terms of index volatility, with 4 lags and 6 lags, it appears that index volatility is still influenced by SVI.

Table 5. Pairwise Granger causality tests for return and volatility of Hastc and Google search volume index.

This table reports the p-values for Granger causality test on Google search volume index and Hastc return and volatility. The data is obtained weekly from December of 2006 to November of 2014. Model specifications include 2 lags, 4 lags and 6 lags.

Lag	Null hypothesis	Prob.
	SVI hastc does not Granger Cause return hastc	0.6082
	Return hastc does not Granger Cause SVI hastc	0.9954
2		
	SVI hastc does not Granger Cause volatility hastc	**0.0022**
	Volatility hastc does not Granger Cause SVI hastc	**0.0677**
	SVI hastc does not Granger Cause return hastc	**0.0725**

4	Return hastc does not Granger Cause SVI hastc	0.9580
	SVI hastc does not Granger Cause volatility hastc	**0.0432**
	Volatility hastc does not Granger Cause SVI hastc	**0.0300**
6	SVI hastc does not Granger Cause return hastc	**0.0181**
	Return hastc does not Granger Cause SVI hastc	**0.0812**
	SVI hastc does not Granger Cause volatility hastc	**0.0881**
	Volatility hastc does not Granger Cause SVI hastc	0.1495

As can be seen in the table, when 2 lags is included in the model specification, Google search volume index is of no use in predicting return of Hastc, but is has effect on the index volatility. In addition, search volume index is likely to change following the change in index volatility. However, with 4 lags, it appears that Google search volume index has effect on both index return and volatility and index volatility also has influence on future SVI. The same results are shown in case of 6 lags. SVI has statistical significant effect on return and volatility. Specially, with 6 lags, return statistically Granger cause Google search volume index with p-value being 0.0812. The results for Hastc is quite different from that of Vnindex. SVI has both impact on Vnindex performance and Hastc performance but the opposite direction, i.e. index performance has influences on SVI is just true in case of Hastc, not Vnindex. It is probably be explained due to the effect of companies' sizes. As mentioned above about the Vietnamese stock market, in the Hanoi Stock Trading Center (HASTC), only small and medium companies are listed. The big companies are listed on Ho Chi Minh Stock Trading Center with the market index is Vnindex. With small and medium stocks, the ability of processing information of investors cannot be quick. Stock returns and volatility change fairly slow with changes in investors' attention. So SVI of four or six weeks before can have impact on today index performance.

Table 6. Pairwise Granger causality test for cross different indexes returns and volatility and Google search volume index.

This table reports the p-values for Granger causality test on Google search volume index and returns and volatility of cross different indexes. The data is obtained weekly *from December of 2006 to November of 2014. Model specifications include 2 lags, 4 lags and 6 lags.*

Lags	Null hypothesis	Prob.
2	SVI hastc does not Granger Cause return vnindex	0.6494
	Return vnindex does not Granger Cause SVI hastc	0.7796
	SVI hastc does not Granger Cause volatility vnindex	**0.0009**
	Volatility vnindex does not Granger Cause SVI hastc	**0.0116**
	Return hastc does not Granger Cause SVI vnindex	0.4227
	SVI vnindex does not Granger Cause return hastc	0.2765
	Volatility hastc does not Granger Cause SVI vnindex	**0.0038**
	SVI vnindex does not Granger Cause volatility hastc	**0.0004**
4	SVI hastc does not Granger Cause return vnindex	0.4715
	Return vnindex does not Granger Cause SVI hastc	0.9553
	SVI hastc does not Granger Cause volatility vnindex	**0.0376**
	Volatility vnindex does not Granger Cause SVI hastc	**0.0002**
	Return hastc does not Granger Cause SVI vnindex	0.6839
	SVI vnindex does not Granger Cause return hastc	0.5129
	Volatility hastc does not Granger Cause SVI vnindex	0.2642
	SVI vnindex does not Granger Cause volatility hastc	**0.0001**
6	SVI hastc does not Granger Cause return vnindex	0.5328
	Return vnindex does not Granger Cause SVI hastc	0.3804
	SVI hastc does not Granger Cause volatility vnindex	0.1942
	Volatility vnindex does not Granger Cause SVI hastc	**0.0089**
	Return hastc does not Granger Cause SVI vnindex	0.5954
	SVI vnindex does not Granger Cause return hastc	0.1819
	Volatility hastc does not Granger Cause SVI vnindex	0.7168
	SVI vnindex does not Granger Cause volatility hastc	**0.0067**

Overall, the table shows that the relationship between Google search volume index and index volatility not only appear within the same index but also across different indexes. To be specified, with 2 lags being included in the model specification, Vnindex and

Hastc volatility are influenced by a change in attention to the Hastc and Vnindex SVI, respectively. And the same situation occur when adding 4 and 6 lags in the model. Changes in investors' attention to one index might cause changes in that index fluctuation (as can be seen in table 4 and 5). Then, it will has effect on investors' forecast on the total market and cause the change in other index volatility. For example, in case of Vnindex, when investors' attention to this index changes due to some bad news revealed, Vnindex's return will fluctuate more. Investors might lose their belief on the total market future, followed by the fluctuation of Hastc also. However, there appears no relationship between Google search volume index and return of cross different indexes.

5.3.2. Properties of attention effect: VAR estimation results

Besides Granger causality test, VAR estimation and the corresponding impulse response functions are applied to determine the sign, timing of the relationship between Google search volume index and indexes' return and volatility.

Table 7. VAR estimation for search volume index and index return

*This table reports results of VAR estimation for Google search volume index (SVI_t) and indexes' return (R_t). Data is obtained weekly from December, 2006 to November, 2014. The indexes are Vnindex and Hastc. In each index, the first column shows results for return equation, and the second column presents results for Google search volume index equation. VAR specifications for Vnindex include 4 lags while VAR specifications for Hastc includes 6 lags. The optimal number of lags is determined by lag length criteria, i.e. LR, AIC, FPE, SC, HQ. The estimated coefficients is followed by standard errors in ( ) and t-statistics in [ ]. *, **, & *** denote significance level at 10%, 5% and 1%, respectively.*

	VNINDEX		HASTC	
	R_t	SVI_t	R_t	SVI_t
R_{t-1}	0.1388*** (0.0497) [2.7929]	-0.3596 (0.5762) [-0.6240]	0.1833*** (0.0506) [3.6220]	0.4412 (0.6816) [0.6473]

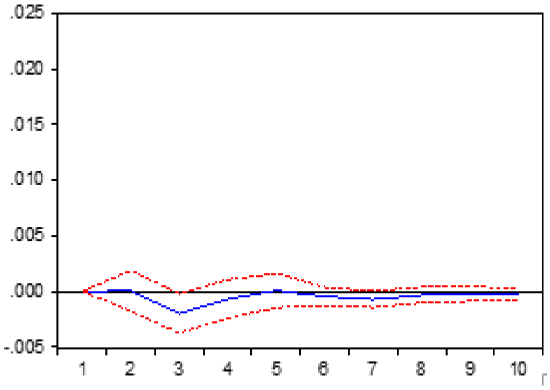
R_{t-2}	0.0092 (0.0501) [0.1829]	0.2185 (0.5814) [0.3758]	-0.0229 (0.0514) [-0.4467]	0.6571 (0.6925) [0.9489]
R_{t-3}	0.0237 (0.0495) [0.4779]	0.4771 (0.5747) [0.8301]	0.0053 (0.0504) [0.1051]	-0.0496 (0.6793) [-0.0731]
R_{t-4}	0.0393 (0.0489) [0.8028]	-0.1625 (0.5669) [-0.2866]	0.0865* (0.0503) [1.7181]	0.1632 (0.6779) [0.2407]
R_{t-5}			0.0299 (0.0503) [0.5948]	1.9348*** (0.6776) [2.8553]
R_{t-6}			-0.0432 (0.0499) [-0.8673]	-0.0712 (0.6715) [-0.1060]
SVI_{t-1}	0.0001 (0.0042) [0.0340]	0.2983*** (0.0493) [6.0519]	0.0035 (0.0038) [0.9302]	0.1340*** (0.0510) [2.6273]
SVI_{t-2}	-0.0093** (0.0043) [-2.1369]	0.0494 (0.0502) [0.9834]	0.0032 (0.0037) [0.8660]	0.2679*** (0.0499) [5.3605]
SVI_{t-3}	0.0008 (0.0044) [0.1858]	0.2228*** (0.0505) [4.4154]	0.0016 (0.0038) [0.4090]	0.1090** (0.0515) [2.1168]
SVI_{t-4}	0.0018 (0.0043) [0.4305]	0.1750*** (0.0494) [3.5449]	-0.0079** (0.0038) [-2.0732]	0.1008** (0.0514) [1.9621]
SVI_{t-5}			0.0052 (0.0038) [1.3761]	0.1975*** (0.0506) [3.9038]
SVI_{t-6}			-0.0093** (0.0038) [-2.4556]	0.1474*** (0.0511) [2.8854]
C	0.0083 (0.0062)	0.3353*** (0.0718)	0.0019 (0.0021)	0.0281 (0.0288)

	[1.3369]	[4.6703]	[0.8803]	[0.9766]
R-squared	0.0385	0.3409	0.0844	0.7188
F-statistic	1.998	2.580	2.935	8.138

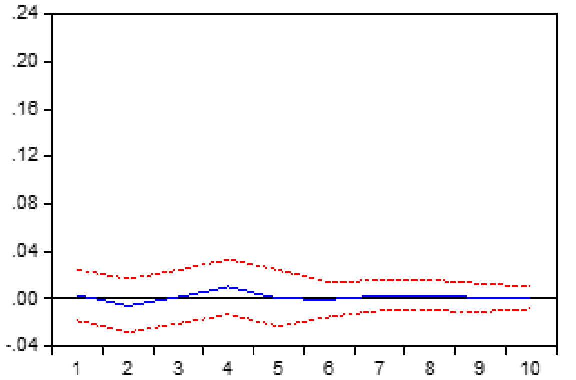
In case of Vnindex, the Google search volume index for Vnindex has rapid negative impact on its return with the second lag of SVI being negatively significant at 5% level of significance. As can be seen in the Figure 1, this impact does not last too long because it converges to zero after a few periods. In contrast, Google search volume index for Hastc has a delayed influence. To specify, SVI of four and six weeks before has significant negative impact on today index return at the level of significance of 5%. The return of Hastc will decrease after an increase of search four and six week ago. This impact disappears more slowly than the impact of SVI on Vnindex return. Overall, an increase in SVI has quick negative effect on large index return, i.e. Vnindex return and has delayed negative effect on small index return. It can be understood that investors process information of large stock return more quickly than small stock.

Table 7 shows that changes in past return of Vnindex do not have significant impact on Google search volume index. However, in case of Hastc, an increase in past return of last five week results in an increase in today Hastc SVI. In addition, this impact last quite long in the market (Figure 1 shows that the impact is slowly converged to zero.) Besides, in both case of Vnindex and Hastc, changes in past SVI is followed by changes in today SVI. This effect is fairly quick and disappears in time slowly.

Response of Vnindex R_t to SVI_t



Response of Vnindex SVI_t to Vnindex R_t



Response of Hastc R_t to Hastc SVI_t Response of Hastc SVI_t to Hastc R_t

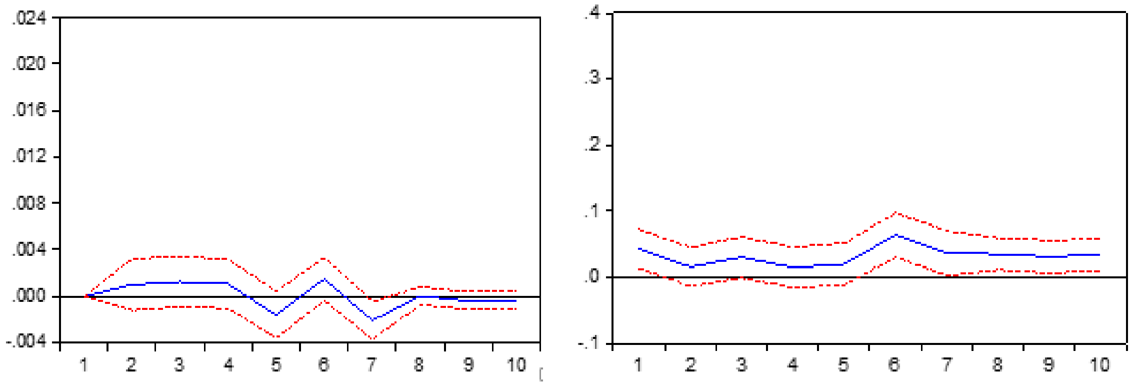


Figure 3. Impulse response function for VAR estimation of Stock index return and Google search volume index.

This figure reports impulse response to Cholesky one standard deviation innovations ±2 standard errors. The 4 lags and 6 lags are included in the VAR estimation for Vnindex and Hastc, respectively. Indexes are Vnindex and Hastc. The data of index return and Google search volume index is obtained weekly from December, 2006 to November, 2014.

Besides index return, next the relationship between index volatility and search is investigated within VAR model. As being analyzed before in Granger causality test, index volatility is likely to change following the changes in Google search volume index. In addition, search volume is also influenced by a change in index volatility. In order to determine how quickly this impact disappear in time, VAR estimation is applied for Google search volume index and index volatility. Table 8 reports the results of this VAR estimations and also impulse response function for VAR estimation of Stock index volatility and Google search volume index is shown in figure 2.

Table 8. VAR estimations for Google search volume index and index volatility.

This table reports results of VAR estimation for Google search volume index (SVI_t) and index volatility (V_t). Data is obtained weekly from December, 2006 to November, 2014. The indexes are Vnindex and Hastc. In each index, the first column shows results for volatility equation, and the second column presents results for Google search volume index equation. VAR specifications for both Vnindex and Hastc include 3 lags. The *optimal number of lags is determined by lag length criteria, i.e. LR, AIC, FPE, SC, HQ. The estimated coefficients is followed by standard errors in ( ) and t-statistics in [ ]. *, **, & *** denote significance level at 10%, 5% and 1%, respectively.*

	VNINDEX		HASTC	
	V_t	SVI_t	V_t	SVI_t
V_{t-1}	0.4051***	3.6769**	0.3541***	2.3609
	(0.0507)	-1.6997	(0.0521)	-1.7679
	[7.9938]	[2.1632]	[6.8027]	[1.3353]
V_{t-2}	0.1251**	-0.6125	0.1827***	-2.7100
	(0.0543)	-1.8227	(0.0544)	-1.8491
	[2.3013]	[-0.3360]	[3.3561]	[-1.4656]
V_{t-3}	0.1461***	1.9348	0.0791	5.2694***
	(0.0499)	-1.6767	(0.0524)	-1.7808
	[2.9234]	[1.1539]	[1.5085]	[2.9589]
SVI_{t-1}	0.0046***	0.3394***	0.0015	0.2489***
	(0.0013)	(0.0450)	(0.0015)	(0.0502)
	[3.4529]	[7.5427]	[0.9944]	[4.9549]
SVI_{t-2}	-0.0021	0.0509	0.0006	0.4022***
	(0.0014)	(0.0482)	(0.0014)	(0.0479)
	[-1.4751]	[1.0565]	[0.4565]	[8.3909]
SVI_{t-3}	0.0010	0.2693***	0.0013	0.2068***
	(0.0014)	(0.0455)	(0.0015)	(0.0502)
	[0.7696]	[5.9207]	[0.8614]	[4.1154]
	-0.0005	0.3849***	0.0037***	0.0159
C	(0.0020)	(0.0666)	(0.0010)	(0.0350)
	[-0.2541]	[5.7821]	[3.6316]	[0.4531]
R-squared	0.4160	0.3889	0.3943	0.7023
F-statistic	4.393	3.925	3.927	1.423

Response of Vnindex V_t to Vnindex SVI_t Response of Vnindex SVI_t to Vnindex V_t

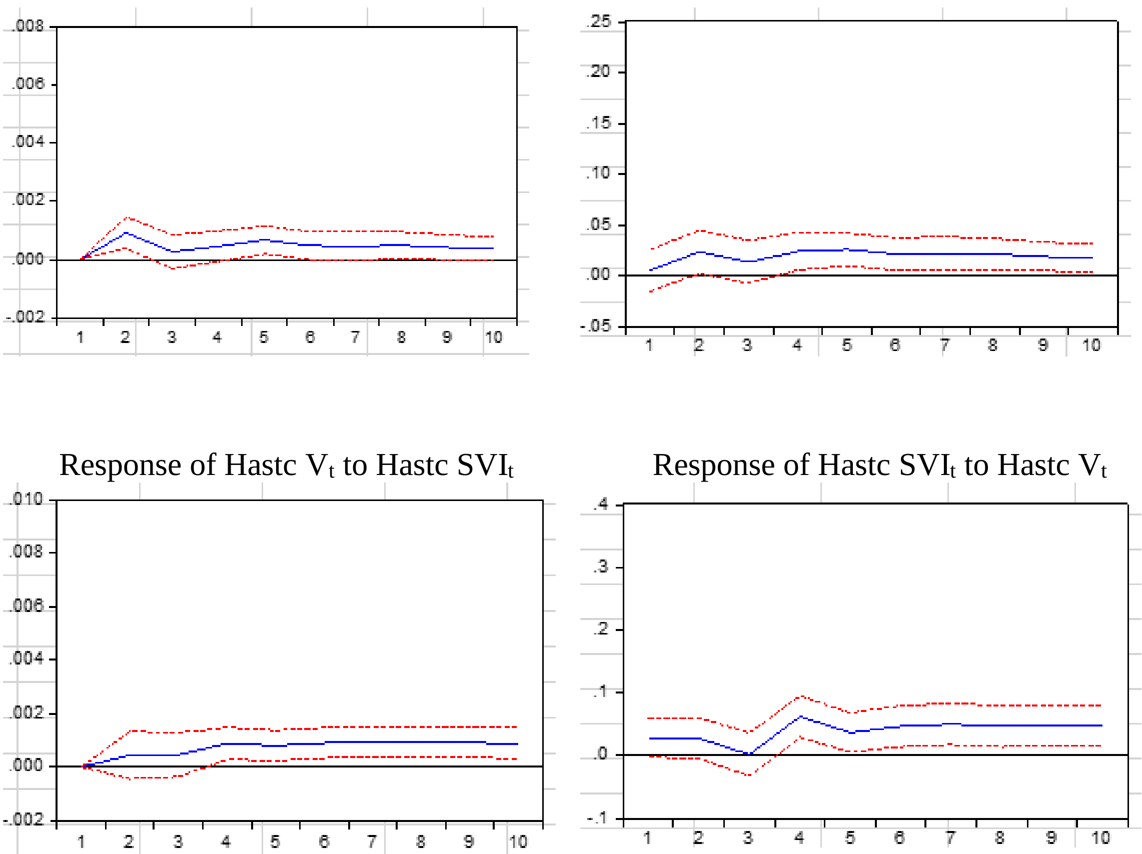


Figure 4. Impulse response function for VAR estimation of Stock index volatility and Google search volume index.

This figure reports impulse response to Cholesky one standard deviation innovations ±2 standard errors. The 3 lags are included in the VAR estimation for both Vnindex and Hastc. Indexes are Vnindex and Hastc. The data of index volatility and Google search volume index is obtained weekly from December, 2006 to November, 2014.

As can be seen in the table 8, search volume index for Vnindex at time t-1, i.e. one week before, has a significant immediate positive impact on the index volatility with the level of significance of 1%. Another saying, the Vnindex volatility rises one week after an increase in its attention. This impact is remembered by the market for quite a long time before converging to zero value. Similarly, Vnindex volatility also has immediate effect on its search (the first lag of volatility is significant at 5% level of significance). Changes in past volatility of Vnindex also fairly quickly affect the index volatility of today. Moreover, there is a postponed impact of past volatility on today volatility (the two and three lags of volatility are significant).

In case of Hastc index, it appears that Hastc volatility and search loose significant with all three lags of search is insignificant. However, the third lag of volatility has a positive significant impact on search. In other words, there is a delayed influence of Hastc volatility on its search volume index. As the impulse response function in figure 2 suggests, this effect take a long time to dissipate.

5.4. Role of attention and predictability of past index returns

5.4.1. The effect of investor attention on index return conditional on the sign of past return and past return.

Table 9. The effect of investor attention on index return conditional on the sign of past return.

*This table reports the OLS estimation results for the impact of search volume index conditional on the sign of past return on indexes return. The dependent variable is indexes return, and independent variables are past returns (R_t), past search volume index (SVI_t) and search volume index conditional on the sign of past return. Dummy variable is equal to 1 if the lagged return is negative and 0 otherwise. The indexes are Vnindex and Hastc. Data is obtain weekly from December, 2006 to November, 2014. *.**, & *** denote significance levels of 10%, 5% and 1%.*

Variable	VNINDEX			HASTC		
	Coeff.	Std. E	Prob.	Coeff.	Std. E	Prob.
C	0.0082	0.0062	0.1847	0.0022	0.0021	0.2936
R_{t-1}	0.1654**	0.0718	0.0218	0.0581	0.0699	0.4068
R_{t-2}	0.0395	0.0723	0.5846	-0.0530	0.0701	0.4500
R_{t-3}	-0.0021	0.0719	0.9759	-0.0692	0.0699	0.3227
R_{t-4}	-0.0059	0.0715	0.9344	0.0897	0.0688	0.1929
SVI_{t-1}	-0.0005	0.0044	0.8998	0.0061	0.0040	0.1254
SVI_{t-2}	-0.0100**	0.0045	0.0264	0.0039	0.0040	0.3356
SVI_{t-3}	0.0015	0.0045	0.7415	0.0037	0.0039	0.3541

SVI_{t-4}	0.0030	0.0045	0.5017	-0.0096**	0.0039	0.0149
$SVI_{t-1}*D(R_{t-1}<0)$	0.0011	0.0020	0.5928	-0.0077**	0.0033	0.0181
$SVI_{t-2}*D(R_{t-2}<0)$	0.0011	0.0020	0.6013	-0.0028	0.0033	0.3968
$SVI_{t-3}*D(R_{t-3}<0)$	-0.0011	0.0020	0.5782	-0.0045	0.0033	0.1726
$SVI_{t-4}*D(R_{t-4}<0)$	-0.0017	0.0020	0.3980	-0.0017	0.0033	0.5991
R-squared	0.0427			0.0926		
Adjusted R-squared	0.0136			0.0644		
F-statistic	1.467			3.290		

The results indicate that Vnindex returns are not influenced by the interaction term between lag search volume and dummy variable. All the coefficients of interaction term are insignificant in case of Vnindex. In other words, it has not had enough evidence to determine that the sign of return in the past, i.e. return in the past is negative or positive, can affect level of the impact of investors' attention on the index return at present. However, the coefficient of the second lag of search volume has negative significant impact on present return at 5% level of significant. If search volume of Vnindex increase by 1%, the value of index return will decrease by 0.01 points after two week.

In terms of Hastc index, it can be seen in the table 9 that the interaction term of the first lag has negative impact on Hastc return at present with the level of significance of 5%. Another saying, if the return of one week before is negative, an increase in the search volume will result in more decrease in the index present return. In addition, the forth lag of search volume also has significant negative effect on return at the present. If the search volume increase by 1%, the index return after four week is likely to decrease by 0.0096 points.

Table 10. The effect of investor attention on index return conditional on past return

This table reports the OLS estimation results for the impact of search volume index conditional on the past return on indexes return. The dependent variable is indexes return, and independent variables are past returns (R_t), past search volume index (SVI_t) and search volume index conditional on the past return. The indexes are Vnindex and

*Hastc. Data is obtain weekly from December, 2006 to November, 2014. *.**, & *** denote significance levels of 10%, 5% and 1%.*

Variable	VNINDEX			HASTC		
	Coeff.	Std. E	Prob.	Coeff.	Std. E	Prob.
C	0.0085	0.0063	0.1791	0.0018	0.0021	0.3928
R_{t-1}	-0.1969	0.2957	0.5059	-0.0975	0.1251	0.4360
R_{t-2}	-0.0533	0.2963	0.8572	0.1791	0.1244	0.1506
R_{t-3}	0.3832	0.2937	0.1927	0.0967	0.1248	0.4389
R_{t-4}	-0.0154	0.2921	0.9580	-0.0094	0.1245	0.9396
SVI_{t-1}	0.0002	0.0043	0.9623	0.0023	0.0036	0.5202
SVI_{t-2}	0.0095**	0.0044	0.0304	0.0019	0.0036	0.5877
SVI_{t-3}	0.0002	0.0044	0.9678	0.0022	0.0036	0.5469
SVI_{t-4}	0.0024	0.0043	0.5707	-0.0099***	0.0036	0.0067
$SVI_{t-1}*R_{t-1}$	0.2292	0.1982	0.2481	0.2646**	0.1042	0.0115
$SVI_{t-2}*R_{t-2}$	0.0449	0.1984	0.8210	-0.1658	0.1048	0.1143
$SVI_{t-3}*R_{t-3}$	-0.2471	0.1967	0.2097	-0.0827	0.1055	0.4330
$SVI_{t-4}*R_{t-4}$	0.0344	0.1955	0.8606	0.1142	0.1043	0.2743
R-squared	0.0450			0.0961		
Adjusted R-squared	0.0160			0.0680		
F-statistic	1.552			3.427		

The coefficients of interaction terms $SVI_{t-i}*R_{t-i}$ in the model in table 10 indicates that with a unit increase in the past return, the impact of search volume will increase or decrease by an amount that equals to the coefficient value. These coefficients also measure the change in the effect of the past returns on the current index return per unit rise in investor attention. It is easily to see that in the table, the coefficient of the first lag interaction term of Hastc is positively significant at 5% level of significance. In other words, if Hastc's return of one week before rises by 1 point, the impact level of its Google search volume on present index return will increase by 0.2646. And it can be understood that the impact of return of one week before on current index return will increase if investors pay more attention on this index.

Moreover, there appears a postponed effect of past Hastc search volume on its return. To specify, the coefficient of the forth lag search volume of Hastc is negatively significant at 1%. It means that 1% increase in search volume four weeks before will result in 0.0099 points decrease in Hastc return at the present.

In contrast, in case of Vnindex, all of the coefficients of interaction terms is insignificant. There is not enough evidence to show that the magnitude of the impact if search volume on Vnindex return depends on a unit change in past index return. Vnindex return is only affected by the second lag of search volume. At the 5% level of significance, 1% increase in Vnindex search volume is followed by 0.0095 points increase in the index return after two weeks.

5.4.2. The effect of investor attention on index volatility conditional on past return

Parallel with index return, the effect of investor attention, which is measured by Google search volume index, on index volatility conditional on past return is examined using interaction term $SVI_{t-i}*R_{t-i}$ in the model specification. The table below shows the results for this estimation.

Table 11. The effect of investor attention on index volatility conditional on past return

*This table reports the OLS estimation results for the impact of search volume index conditional on the past return on indexes volatility. The dependent variable is indexes volatility, and independent variables are past returns (R_t), past volatility (V_t), past search volume index (SVI_t) and search volume index conditional on the past return. The indexes are Vnindex and Hastc. Data is obtain weekly from December, 2006 to November, 2014. *.**, & *** denote significance levels of 10%, 5% and 1%.*

Variable	VNINDEX			HASTC		
	Coeff.	Std. E	Prob	Coeff.	Std. E	Prob.
C	-0.0004	0.0021	0.8525	0.0041***	0.0010	0.0001
V_{t-1}	0.4021***	0.0519	0.0000	0.3393***	0.0527	0.0000
V_{t-2}	0.1093**	0.0552	0.0484	0.1882***	0.0549	0.0007
V_{t-3}	0.1384**	0.0551	0.0125	0.0876	0.0557	0.1163
V_{t-4}	0.0344	0.0507	0.4985	-0.0129	0.0524	0.8058

R_{t-1}	-0.0649	0.1123	0.5636	-0.0669	0.0515	0.1950
R_{t-2}	$-6x10^{-5}$	0.1005	0.9995	0.0740	0.0519	0.1552
R_{t-3}	0.0273	0.1004	0.7853	-0.1438***	0.0527	0.0066
R_{t-4}	0.1299	0.0985	0.1878	-0.0095	0.0520	0.8559
SVI_{t-1}	0.0039**	0.0016	0.0123	0.0024	0.0015	0.1221
SVI_{t-2}	-0.0021	0.0015	0.1438	-0.0005	0.0015	0.7583
SVI_{t-3}	0.0010	0.0015	0.4944	0.0016	0.0015	0.3034
SVI_{t-4}	0.0005	0.0014	0.7176	-0.0004	0.0015	0.7857
$SVI_{t-1}*R_{t-1}$	0.0408	0.0755	0.5892	0.0467	0.0440	0.2889
$SVI_{t-2}*R_{t-2}$	0.0072	0.0675	0.9152	-0.0316	0.0445	0.4779
$SVI_{t-3}*R_{t-3}$	-0.0029	0.0675	0.9649	0.1430***	0.0444	0.0014
$SVI_{t-4}*R_{t-4}$	-0.0785	0.0659	0.2346	0.0123	0.0431	0.7762
R-squared	0.4263			0.4239		
Adjusted R-squared	0.4001			0.3971		
F-statistic	1.630			1.578		

Similarly with the case of estimating effect of search volume on Vnindex return conditional on past return, the table above shows that in testing the relationship of SVI on Vnindex volatility conditional on past return, all the coefficients of the interaction terms in the model of Vnindex are insignificant. It indicates that the impact level of search volume on index volatility seem to be not affected by a unit change in Vnindex returns. In case of Vnindex, past index return has no use in predicting future return volatility. Besides, the coefficient of the first lag of Vnindex search volume is positive and significant at 5% level of significance. With more attention is paid to this index, index return volatility will increase after just one week. Past index volatility also has influence on today volatility. Coefficients of the first, the second and the third lag of index volatility are positive and significant.

In terms of Hastc, the effect magnitude of search volume will change if the third lag index return change by one unit. In specification, if Hastc return of the last three week increase by 1 unit, the impact of search volume on index volatility will increase by 0.143 unit. It also suggests that the effect of past index return on index volatility will increase if investors pay more attention on this index. Besides, past return itself has negative effect on index volatility. The coefficient of the third lag of index return or return of three week before is negative and significant at the level of 1%. One unit increase in index return of three weeks before is followed by 0.1438 units decrease in index volatility.

6. CONCLUSION

This study investigates the impact of investors' attention, which is measured by the Google search volume index, on the stock market performance, i.e. stock return and volatility in the Vietnamese stock market. Many researchers have conducted their studies related to this relationship recently. It is said that investors' attention might drive the market return and volatility and play a role in asset return and the efficiency of market (Vozlyublennaia, 2014). Barber & Odean (2008) stated that when searching information about the stock that investors want to buy, they face with the difficulty that there are thousands of stocks in the market, which limit the capacity to process information of investors. They might pay more attention on some stocks and ignore other stocks. They are likely to buy stocks that have first caught their attention even they are not stocks that have the best performance in the stock market. As a results, the stock prices are changes following changes in investors' attention. In addition, in the market, individual investors are traders who most frequently use Google to look for information about stocks. Therefore, the investors' attention is mostly capture for the individual investors' attention.

In the Vietnamese stock market, there are two stock exchange centers including Ho Chi Minh and Hanoi Stock Trading Center. Only stocks of big companies are listed on Ho Chi Minh Stock Trading Center (HOSE). Small and medium companies are listed on Hanoi Trading Center (HASTC). Vnindex represents a basket of typical stocks on HOSE and it indicates the fluctuation of stock price listed on HOSE. Besides, Hastc represents for stocks on Hanoi Trading Center. These two indices are examined in this study. In Vietnames stock market, the number of individual investors is much more than the number of mutual fund, hedge, and fund management companies, etc. Unlike professional trading companies, individual investors tent to use Internet to find information and use that information to trade in the market. Therefore, in case of Vietnamese stock market, individual investors' attention is likely to have significant effect on stock return and volatility. That is the reason while Vietnam is chosen to test this effect.

Following the method of previous studies, the Granger causality test, VAR estimation model and OLS method are applied in order to test whether investors' attention is useful in predicting stock market performance, the sign and timing of this effect as well as the magnitude of this effect conditional on the sign of past return and also the past return.

In terms of Vnindex, the results suggest that investors' attention which is measured by Google search volume index Granger cause both index return and volatility when two lags are added in the model specification. Moreover, the impact of search volume on Vnindex return and volatility is fairly quick and the impact disappears in time in only a few period. A change in investors' attention on the stock will result changes in stock performance after only one or two week. However, a unit change in past index return does not affect the impact on search volume on index performance as well as change in search volume have no effect on impact level of the past return. In other words, the predictability of past return is not influenced by investors' attention. This result is not in line with the results of Vozlyblennaia (2014) which suggests that an increase in investors' attention diminishes the predictability of past return.

In terms of Hastc, it appears that there is a delay in the impact of search volume on index return and volatility. When four and six lags are included in the model, both index return and volatility are affected by investors' attention. To specify, if there is an increase in search volume for Hastc, the index return will decrease after four weeks and continuosly decrease after six weeks. This effect takes a long time to dissipate in the market. Besides, if the past return of Hastc is negative, the effect of search volume on the index return will increase. And with a unit increase in past return, effect of search on index volatility also increases. In the opposite direction, the impact level or predictability level of the past return on recent return and volatility will rise if investors pay more attention on the index. In case of Vietnamese stock market, investors' attention cannot help improve market efficiency if return predictability is interpreted as a form of market inefficiency.

Overall, in Vietnamese stock market, investors' attention has a role in predicting stock performance. The effect of attention on stock large companies (Vnindex) seems to be more rapid than effect on small and medium companies (Hastc). However, this effect is remembered by the market longer in case of small and medium companies. Besides, while the impact level of search volume on index performance increase conditional on a unit increase in return of Hastc, there has not had enough evidence to prove that past index return has influences on impact magnitude of search volume in case of Vnindex.

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