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Google Search intensity and stock returns in frontier markets: Evidence from the Vietnamese market[1]

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Abstract

The study investigates the impact of investor attention on stock trading by modeling the relationship between Google Search intensity and stock return with stocks listed in frontier markets in Vietnam from October 2016 to October 2021. The study has three findings. First, the study confirms the price pressure hypothesis and attention theory that Google Search intensity positively affects stock returns. Second, this study indicates that the impact of Google Search intensity on stock price is short-term. The positive effect is within the week of searching and reverses the following week, although the reverse force is not strong. Third, the relationship is more robust during COVID-19 than in the prepandemic period, suggesting that after a shock, more new

Keywords

- investor attention
- search intensity
- Google Search
- stock returns
- frontier markets
- Vietnam
- COVID-19

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[1] This is the extended version of Khanh, T. Q., Hoai, N. T., Duc, D. T. V., & Nguyen, D. P. (2022, November 24–26). *Effects of investor via Internet search intensity on stock market: Evidence in Vietnam market*. International Symposium on Sustainable Development in Transition Economies, Hanoi, Vietnam.

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individual investors enter the market, the impact of GSVI on stock return is more substantial.

JEL codes: D53, G1, G4

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Introduction

The efficient market hypothesis (EMH) formulated by Fama (1970) holds that stocks are always traded at their fair value on exchanges. Therefore, investors cannot outperform the market through fundamental or technical analysis methods. Although the EMH is the cornerstone of modern financial theory, it is still the subject of many questions and controversies. The EMH assumes that all investors perceive all available information similarly. However, Merton (1987) argued that investor recognition was essential in pricing and determining stock liquidity. The reason was that potential investors must recognise the company before becoming familiar with it and ultimately making investment decisions. Using various methods to analyse and value stocks, each investor would judge a stock's growth potential differently. Thus, the same stock was not perceived in the same way by different investors. On the other hand, according to the EMH, a stock valuation and analysis system was available to all investors, and their access to the system must be equal. However, there are always significant disparities between institutional and individual investors in the ability to access, collect, synthesize, and analyse information. Barber and Odean (2007) stated that individual investors would inevitably buy stocks that attracted their attention due to their financial and time constraints. The statement is called attention theory (AT). Individual investors' buying decisions led to temporary fluctuations in stock returns. However, their attention did not affect selling decisions because they could only sell what they had.

Because attention cannot be measured, choosing an appropriate proxy for it is challenging for researchers. Today, as the Internet becomes ubiquitous and easily accessible, individual investors express their interest in a particular stock by using search engines or referencing online forums. When investors are interested in a particular stock, they tend to seek information about that stock to a greater extent. This means that search volume can be used as a direct proxy for investor attention. This proxy is used in many studies, such as those by Da et al. (2011), Siganos (2013), Aouadi et al. (2013), Bijl et al. (2016), Takeda and Wakao (2014), Kim et al. (2019), Perlin et al. (2017), Smales (2021), Costola et al. (2021). Although these authors use different keywords, they conclude that the Google Search Volume Index (GSVI) is a suitable tool to test the relationship between the attention of investors and financial markets.

Several studies on the relationship between investor attention expressed through GSVI and the stock market were conducted for single markets (Ekinci & Bulut, 2021; C. Nguyen et al., 2020; Swamy & Munusamy, 2019) or expanded to an international level (Akarsu & Süer, 2021; Chen, 2017; Tantaopas et al., 2016). However, there are still three research gaps that need filling.

First, the studies mentioned above focus on advanced and emerging financial markets rather than frontier markets. Frontier markets are less established than emerging markets. In frontier markets, information transparency and the effectiveness of regulations are lower (Vo & Phan, 2019). Frontier markets have few large companies, and foreign investor activity is significantly restricted. Thus, most investors are domestic individuals. Because these investors lack access to complex and professional information sources, they rely on available and free information sources like Google. Therefore, studying the relationship between GSVI and stock market volatility in these frontier countries will be significantly meaningful.

Second, studies on the relationship between investor attention and price movements in frontier markets have not reached a consensus of conclusions. For example, both C. P. Nguyen et al. (2019) and C. Nguyen et al. (2020) use data from the Vietnamese market to find the relationship between GSVI and stock return. However, while C. Nguyen et al. (2020) concluded a positive relationship between these two variables, C. P. Nguyen et al. (2019) proved the relationship in the opposite direction. Another study by Osarumwense (2020) shows that investor attention does not impact stock returns in the Nigerian market. Therefore, more research should be conducted for frontier markets to provide further evidence about the relationship between search intensity and stock prices and to point out the reasons for different study results.

Vietnam can be a typical frontier market in which to study the impact of investor attention through GSVI on the stock price. According to the State Security Commission of Vietnam, the proportion of individual investors in Vietnam is 99.4% (State Security Commission of Vietnam, 2022). By 2022, the percentage of the population using the Internet in Vietnam is 77.38%

(Statista, 2023), and Google is the most popular search engine, accounting for 91.8% market share (Statcounter, 2022). Because individual investors lack the knowledge and financial capability to gather information, they often refer to their friends or Google Search engines to make decisions.

Third, studies on the impact of GSVI and the stock market have not mentioned the difference between market conditions, especially during the COVID-19 pandemic. "During COVID-19" refers to the two years after the COVID-19 breakout in Vietnam. Negatively affected by the COVID-19 pandemic, many Vietnamese businesses had to reduce the scale of their operations or go bankrupt. According to the General Statistics Office of Vietnam, 19,800 enterprises had to withdraw from the market in 2021, an increase of 17.8% compared to 2020 (Vy Vy, 2021). A similar situation emerges worldwide and predicts a decline on stock markets. However, unexpectedly, Vietnam's stock market grew strongly. On the Ho Chi Minh City Stock Exchange, during COVID-19, the number of individual accounts increased by 2.26% a month, and the trading volume was VND 17,472 billion/month, while in the pre-COVID-19 period, these figures were only 0.92% and 3,988 billion VND/month, respectively (State Securities Commission of Vietnam, 2022). Search frequency for stocks also increased, showing that Vietnamese investors pay more attention to the stock market and consider it a promising new investment channel. Changes in market conditions provide a natural context for testing and analysing the rigor of the relationship between GSVI and stock returns. Khanh et al. (2022) investigate the effects of investor behavior via Internet search intensity on the Vietnam stock market. Using the date when the first case of COVID-19 was discovered in Vietnam, this study moved one step further to divide the data into two research periods: before and during COVID-19.

In summary, this study aims to test the investor recognition hypothesis of Merton (1987) and the investor attention theory of Barber and Odean (2007) in the case of a frontier market. Furthermore, the authors seek to establish the various effects of investors' attention on stock returns in different market conditions, specifically before and during the COVID-19 pandemic. Lastly, the research aims to propose essential implications for businesses and investors in the Vietnamese market and other frontier stock markets. In addition to corporate factors, investors can consider GSVI as an indicator to support their stock investment decisions.

After the Introduction, the rest of the paper is organized as follows: A review of the theories and empirical studies is presented in Section 1. Section 2 provides details of the models and datasets. Section 3 discusses the study's results, and the last Section comprises the conclusion and implications.

1. Literature review

Both Merton's investor recognition hypothesis (1987) and Barber and Odean's investor attention theory (2007) acknowledge the existence of the "investor attention" factor but disagree on the effect of this factor on stock returns. Merton (1987) argues that gathering information about stocks requires many resources, so investors will save these resources by tracking only certain stocks. Investors will not buy stocks they do not follow, even if they attract their attention. In contrast, Barber and Odean (2007) argue that investors tend to buy stocks that attract their attention because they face significant challenges in evaluating stocks when deciding to buy. Increased investor attention creates greater buying pressure, causing stock prices and yields to rise but decline afterwards. This argument presented by Barber and Odean (2007) is relevant to individual investors because they tend to access freely available information sources. Attention has little effect on selling because individual investors can only sell available stocks.

Much research has been done to find empirical evidence for these two hypotheses. Because attention cannot be measured, choosing an appropriate representative is challenging for researchers. In the past, indirect measures have been used. The researchers used advertising costs (Grullon et al., 2004; Vorkink et al., 2010), frequency of company reports (Peress, 2008; Rao et al., 2010), and trade volume (Gervais et al., 2001), and profitability (Loh, 2010). However, these proxies have limitations because investors may not notice them (Bank et al., 2011).

Black (1986) stated that noise traders trade on noise signals like information. EMH confirmed no correlation among noise traders because transactions based on noise signals are random, and they will cancel each other out. However, if many investors act on the same signal, there will be a correlation between them, which can be called herd instinct. Herding is the tendency for independent dealers to buy or sell the same security over a period of time. Herding exists among individual investors because they rely on the same signal (Shleifer & Summers, 1990). They are also more sensitive to new trends in their investment decisions (Long et al., 1990). Along with the development of the Internet, online search engines appeared and quickly became effective assistants for individual investors in finding information about stocks they were interested in. When investors utilize the same sources of information, there could be a correlation among them.

The more attention investors pay to a particular stock, the more information investors want to collect to make investment decisions. Therefore, Internet search intensity is used by many scholars as a direct proxy for investor attention in their research. A few scholars use search volume of web browsers—Baidu (Shen et al., 2017; Zhang et al., 2013) or Yahoo (Lawrence et al., 2016;

Mangold et al., 2005). However, most other studies use GSVI as a proxy for investor attention, since this is the world's most popular search engine. Baidu and Yahoo have only small global market shares, 0.5% and 1.1%, respectively, while the share of Google is 92.8% (Statcounter, 2023).

Pioneering studies have been conducted in the context of developed stock markets, but scholars are yet to draw consistent conclusions about how GSVI correlates with the stock market. Many scholars use US market data to assert that search frequency has a positive relationship with stock returns (Da et al., 2011; Joseph et al., 2011; Vlastakis & Markellos, 2012). Research by Bank et al. (2011) for the German market, Takeda and Wakao (2014) for the Japanese market, and Aouadi et al. (2013) for the French market also obtained similar results. Not only stock returns but also stock trading volume increases as the search frequency for stocks increases (Preis et al., 2010; Vlastakis & Markellos, 2012). These conclusions generally support the investor attention hypothesis developed by Barber and Odean (2007). However, other studies reveal contrasting results. Kim et al. (2019) assert that although GSVI can help predict increases in volatility and trading volume of stocks, it cannot help predict future returns on the Norwegian market. Bijl et al. (2016) assert that investor attention harms US stock returns. Using Korean market data, Pyo's research (2017) also shows that investor attention lowers KOSPI returns. Perlin et al. (2017) researched four developed countries, namely the US, UK, Australia, and Canada, and used keywords related to the stock market, in general, such as "stocks," "finance," and "market". They found that the search volume of some keywords was negatively correlated with the overall market return.

Other studies devoted to emerging markets have also reached mixed conclusions. Investor attention positively affects the growth of stock returns in markets such as Malaysia and Indonesia (C. P. Nguyen et al., 2019) and Turkey (Ekinci & Bulut, 2021). In contrast, scholars argue that the more attention an investor pays to a security, the less likely it is that its returns will increase. This was found in Swamy and Munusamy's (2019) study for the Indian market, research by C. P. Nguyen et al. (2019) in the case of the Philippines and Thailand, and by Shen et al. (2017) for the Chinese market.

Instead of just focusing on a few specific markets, some other researchers have expanded their research scope to an international scale, with their aim being to establish the factors that affect the relationship between investor attention and stock returns. Akarsu and Süer (2021) researched 31 markets and found that investor attention is more significant in individualist countries, countries with a psychological avoidance of instability, and developed countries. Tantaopas et al. (2016) examined the impact of investor attention on returns in 10 Asia-Pacific countries. They found that, in most cases, investor attention does not affect indices of return, volatility, or volume but does predict returns because attention will lead to more explicit information-based decisions. Chen (2017) conducted a comprehensive study of 67 countries and concluded that investor attention has a significantly negative effect on stock returns. It is worth noting that this study adds the emotional variable of the market and confirms that more positive market sentiment will make investors pay more attention and vice versa. These findings by Chen (2017) confirm Merton's investor perception hypothesis. Studying various US, European, and emerging markets, Duz Tan and Tas (2021) assert that social media sentiment can help investors build their investment strategies. On the other hand, positive sentiment on Twitter is more evident in small and emerging market companies, which is consistent with the literature that small companies are challenging to value, and emerging market companies have a high level of information asymmetry.

Some other researchers are interested in examining market volatility when a powerful force, such as a pandemic or war, occurs. The study by Kropiński and Anholcer (2022) uses keywords related to uncertainty about Polish economic policy and divides the research data into two periods before and after COVID-19. This study's results show that an increased empirical relationship was confirmed between 12 EPU-related terms and market changes in the second period compared to six terms in the pre-COVID period. The study by Gheorghe and Panazan (2023) aims to quantify the volatility caused by the military conflict between Russia and Ukraine by analysing stock market indices across 40 countries. The results demonstrate that conflict shocks affect stock markets globally. The implications of these findings are significant for investors, decision-makers, portfolio managers, investment funds, and central banks.

Only a few studies have been done on frontier markets. A study by Osarumwense using Nigerian data (2020) concluded that GSVI is not a driving factor for stock price movements and has no interaction with earnings, volume, and volatility when determining price dynamics. Studies by C. Nguyen et al. (2020) and C. P. Nguyen et al. (2019) classified Vietnam as an emerging market, although MSCI (2022) classified Vietnam as a frontier market. Conclusions about the effect of investor attention on stock returns in the Vietnam market differ between the two groups of authors. While C. P. Nguyen et al. (2019) suggested that the higher the search frequency, the lower the stock return, C. Nguyen et al. (2020) obtained the opposite result. The multinational studies by Akarsu and Süer (2021) and Chen (2017) also refer to frontier markets but only analyse at the market level, not at the stock level. On the other hand, rather than delve into the differences between markets, these studies aim to understand the influence of non-economic factors such as emotions and culture on the relationship between investors' attention and the stock market.

According to the market classification framework of MSCI (2022), in emerging markets, the ease of capital inflows and outflows and the effectiveness of the operational framework are significant. Meanwhile, in the frontier markets, the level to which these criteria are fulfilled is only partial or very modest. On the other hand, the quantified requirements for the number and size of large companies in these two market groups are also significantly different. Accordingly, in the frontier markets, there are not many large companies, and the activities of foreign institutional investors are limited, leading to the vast majority of investors being individuals. Google Search further proves its role in helping investors find information. In other words, the Vietnamese market provides an ideal context to test the investor attention hypothesis of Barber and Odean (2007).

The emergence and outbreak of the COVID-19 pandemic seriously affected global socio-economic activities. New market conditions were established and these attracted the attention of many scholars. Many authors have explored the extent of the pandemic's impact on different business sectors. Ding et al. (2020) investigated the daily closing prices of 1,567 stocks listed on NASDAQ and classified these companies into 37 sectors and found that GSVI has a positive correlation with the stock price of the group with a high level of digital conversion stock price but has a negative impact on the stock price of the group with medium and low digital conversion. Lee (2020) also divided the sample into 11 industries and found that the stock index of the IT and healthcare sectors increased, while the overall market index of the S&P500 and the stock index of the remaining industries decreased during the COVID-19 period.

Although most studies agree that a higher GSVI makes the market more volatile, the conclusion about the correlation between GSVI and stock prices and returns during the COVID-19 pandemic is different. A positive relationship is found in Japan and Singapore (Vasileiou, 2021). The negative effect on stock returns can be found in the studies by Shear et al. (2021), Smales (2021), Chundakkadan and Nedumparambil (2022), and Costola et al. (2021). Smales (2021) further argues that individual investors are not looking for information about potential stocks to buy, as argued by Barber and Odean (2007), but are looking for answers to attitudes about the economy and Financial and Economic Attitudes Revealed by Search (FEARS) of households as suggested by Da et al. (2011). Costola et al. (2021) found no relationship between investor attention to the pandemic and the volatility of the French and British stock markets. However, they also find interesting evidence in the Italian situation, where the country's GSVI serves as a precursor and helps to explain yield fluctuations in other countries. Furthermore, the impact of GSVI was also more robust, corresponding to the different periods of the blockade in Italy. Studies have focused on the impact of GSVI on the stock market during the COVID-19 outbreak; however, no studies compare this impact before and during COVID-19 to see how this impact changes as market conditions change.

2. Model specification and data

2.1. Model specification

The study builds a model of the influence of GSVI on stock prices based on the Fama-French three-factor model (FF3FM). Studies such as those by Fang et al. (2017), C. Nguyen et al. (2020), and Khoa and Huynh (2023) proved the higher validity of FF3FM for the Vietnamese stock market compared to other similar models such as CAPM and CF4 (Carhart Four Factor Model).

This paper carries out two types of analysis after statistics analysis. First, the aim is to determine whether there is a difference in the abnormal returns of highly searched-for and less searched-for securities, we run the FF3FM model for different portfolios and a hedge portfolio according to their GSVI. Second, we run the model at the stock level with the entire study sample.

As pointed out in the Introduction, in the five years of research data, the Vietnamese stock market has experienced two distinct periods, which is due to the impact of the COVID-19 epidemic. Therefore, with each model in the two analysis steps above, we divide it into two periods, before COVID-19 and during COVID-19, to see how environmental factors affect the relationship under consideration.

2.1.1. Group regressions

In this section, following Takeda and Wakao (2014) and C. Nguyen et al. (2020), we categorize stocks into four quartiles based on their search index: Q1 is the group with the lowest search intensity, while Q4 is the group with the highest search intensity. Q41, called the hedge portfolio, is the combined portfolio of both Q4 and Q1. The hedge portfolio Q4-Q1 whose strategy is on the long position on the most-searched-for stocks (Q4) and the short position on the least-searched-for stocks. These groups are rebalanced weekly. We then estimate the abnormal returns by applying the FF3FM to the four groups and the hedge portfolio according to Equation (1).

$$R_{p,t} - R_{f,t} = \alpha + \beta_m(R_{m,t} - R_{f,t}) + \beta_s SMB_t + \beta_h HML_t + \varepsilon_{i,t} \tag{1}$$

R_p is the weekly portfolio return, R_f is the risk-free rate, and R_m is the weekly market return. The portfolio return is the average of the securities returns in the portfolio. SMB is the difference between the weekly returns of the small and large stock portfolios. HML is the difference between the weekly returns of high and low book-to-market portfolios. According to FF3FM, small and value stocks tend to have higher risk premiums. In Equation (1), parameter α is the weekly abnormal return of the portfolio.

To assess the models, we follow Takeda and Wakao (2014) and C. Nguyen et al. (2020) and use three proxies for search intensity, including lnGSVI, ΔlnGSVI, and AGSVI. The validity of search intensity comparison among stocks may be severely affected by large shocks; therefore, using ΔlnGSVI and AGSVI can mitigate this problem (Takeda & Wakao, 2014). $\Delta \mathrm{lnGSVI}_t$ measures the change in search intensity over week *t* and is computed as follows:

$$\Delta \mathrm{lnGSVI}_t = \mathrm{lnGSVI}_t - \mathrm{lnGSVI}_{t-1}$$

AGSVI_t measures the abnormal level of search intensity:

$$\mathrm{AGSVI}_t = \mathrm{lnSGSVI}_t - \mathrm{median}(\mathrm{lnSGVI}_{t-1}, \ldots, \mathrm{lnGSVI}_{t-7})$$

The group regression is performed three times, as we use three proxies for search intensity. Additionally, we run the models in two phases, before and after the COVID-19 outbreak, to observe changes in the portfolios' abnormal returns.

2.1.2. Stock-based regressions

Short-term model

Based on the FF3FM applied to each stock, we include the search intensity variable in addition to the other variables to determine whether search intensity can explain the stock returns. The model equation is as follows:

$$R_{i,t} - R_{f,t} = \alpha + \delta GSVI_{i,t-j} + \beta_m(R_{m,t} - R_{f,t}) + \beta_s SMB_t + \beta_h HML_t + \varepsilon_{i,t} \quad (2)$$

where $GSVSI_{i,t-j}$ is the search intensity for stock i with lag j. Some studies, such as C. Nguyen et al. (2020), C. P. Nguyen et al. (2019), Da et al. (2011), and Joseph et al. (2011), included a lag for the variable SI, assuming that stocks had been initially observed and analysed for a period before investing decisions were taken place rationally, which usually led to a higher stock return. However, Ekinci and Bulut (2021) and Takeda and Wakao (2014) found no relationship between searches made in period $t-1$ and stock returns in period t. Ekinci and Bulut (2021) confirmed the relationship between non-lagged search intensity and stock returns. We believe that Ekinci and Bulut's (2021) results were reasonable because, on modern stock markets with effective information systems, investors' decisions are often executed simultaneously on receipt of the information or after only a very short delay. This finding aligned with Barber and Odean's (2008) statement that individual investors were net buyers of stocks with extremely high or low previous-day returns.

As a result, we believe that the relationship between the non-lagged $GSVI$ and Ri may be more robust. Owing to the limitations of the $GSVI$ data, which is only available weekly, we cannot determine the daily lag of the $GSVI$ variable. Therefore, we run model (2) as non-lagged with $GSVI0$ variable and as including 1-period lag with $GSVI$(-1) variable.

Long-term model

According to Barber and Odean (2008), the effect of investor attention on increasing stock returns through buying is temporary. Subsequently, investors adjust their investment behavior based on complete information, resulting in decreased stock returns. To examine the long-term effect of search intensity on stock returns, we run the long-run effect model described in Equation (3). In this equation, lag j of the $GSVI$ variable ranges from 1 to n; statistical standards AIC and BIC are used to determine n in the models (Akaike, 1998).

$$R_{i,t} - R_{f,t} = \alpha + \sum_{k=1}^{n} \delta_k GSVI_{i,t-j} + \beta_m (R_{m,t} - R_{f,t}) + \beta_s SMB_t + \beta_h HML_t + \varepsilon_{i,t} \quad (3)$$

Models with substituted variables

In Equations (2) and (3), the regression of all returns over the period on the factor loadings of the FF3FM assumes that the beta factors of all stocks are identical. To mitigate this issue, we follow Takeda and Wakao (2014) and C. Nguyen et al. (2020) and substitute SMB with firms' capitalization (MK) and HML with firms' price-to-book ratio (PB). We use Equation (4) instead of Equation (2) and Equation (5) instead of Equation (3).

$$R_{i,t} - R_{f,t} = \alpha + \delta GSVI_{i,t-j} + \beta_m (R_{m,t} - R_{f,t}) + \beta_s MK_t + \beta_h PB_t + \varepsilon_{i,t} \quad (4)$$

$$R_{i,t} - R_{f,t} = \alpha + \sum_{k=1}^{n} \delta_k GSVI_{i,t-k} + \beta_m (R_{m,t} - R_{f,t}) + \beta_s MK_{i,t} + \beta_h PB_{i,t} + \varepsilon_{i,t} \quad (5)$$

2.2. Data

This study used data from securities listed on the Ho Chi Minh City Stock Exchange (HOSE), Vietnam's largest stock exchange. The data was obtained for five years, from October 9, 2016, to October 3, 2021, which totals 260 weeks. The market had 402 listed companies as of October 2021.

The $GSVI$ was obtained from Google Trends for the G*SVI* variable for the keyword "stock tickers." While there may be various reasons for individuals to search online for a company's ticker, Joseph et al. (2011) argue that the effort required to process the results of such a query is only worthwhile for someone genuinely considering an investment decision. In contrast, searching for other terms, such as company name, yields a range of information that cannot be related to investment decisions (e.g., product information and store location). GSVI is a weekly index with values ranging from 0 to 100 over a 5-year collection period. The search command was restricted to Vietnam to filter search data of other countries, which could have been performed for various reasons unrelated to security investigation. The GSVI data were filtered to ensure the search keywords were associated with the target stock ticker. Each keyword search result was manually cross-checked against related queries. A stock ticker was considered disqualified if the first 5/10 related queries were unrelated to a company or securities investment; the same key-

Table 1. Data statistics

Pre-COVID-19					
Variable	**Number of observation**	**Mean**	**Standard deviation**	**Min**	**Max**
$R_i - R_f$	24.578	0.0013	0.0542	–1.0009	0.9505
$R_m - R_f$	26.660	0.0011	0.0217	–0.0923	0.0548
R_f	26.660	0.0009	0.0001	0.0005	0.0012
$GSVI_i$	26.660	22.1595	19.8398	0	100
SMB	26.505	0.0004	0.0139	–0.0477	0.0353
HML	26.505	–0.0010	0.0117	–0.0270	0.0311
MK_i	24.627	28.4096	1.8574	23.9775	33.6671
PB_i	23.711	0.0001	0.0008	–0.0041	0.0035
During-COVID-19					
$R_i - R_f$	13.426	0.0087	0.0657	–1.0004	0.4006
$R_m - R_f$	13.640	0.0044	0.0329	–0.1459	0.0794
R_f	13.640	0.0005	0.0001	0.0004	0.0007
$GSVI_i$	13.640	31.1488	21.2913	0	100
SMB	13.640	0.0014	0.0140	–0.0291	0.0376
HML	13.640	0.0012	0.0159	–0.0365	0.0441
MK_i	13.432	28.6564	1.9065	24.2840	33.8125
PB_i	13.361	0.0001	0.0007	–0.0022	0.0035

Source: own work.

words were searched, but for different purposes. After filtering, the sample includes 155 securities.

Companies' stock and financial data were obtained from the Refinitiv database of Thomson Reuters. These data were collected weekly for consistency with the GSVI data. The risk-free rate of return was derived from 10-year government bond yields from the State Bank of Vietnam. We consider January 23, 2020 as the benchmark to divide the data sample, as it marks the date when the first case of COVID-19 was detected in Vietnam. The sample period before the COVID-19 outbreak serves as a normal trading stock market. The COVID-19 period witnessed a change in market conditions, where several new individual investors entered the market for the first time, and market transactions surged. Stata 16 was used to implement the regression models.

Table 1 summarizes the statistics of the key variables of the models divided into the two research periods. There are notable changes in the means of the variables between the two periods. While the risk-free rate R_f witnesses a slight decline, stock premium $R_i - R_f$, market premium $R_m - R_f$, and GSVI$_i$ tend to rise from the pre-COVID-19 to the during-COVID-19 period. Figure 1 displays the variation in the GSVI over time. The SMB has a positive mean, which suggests that small company securities have higher returns than large company securities.

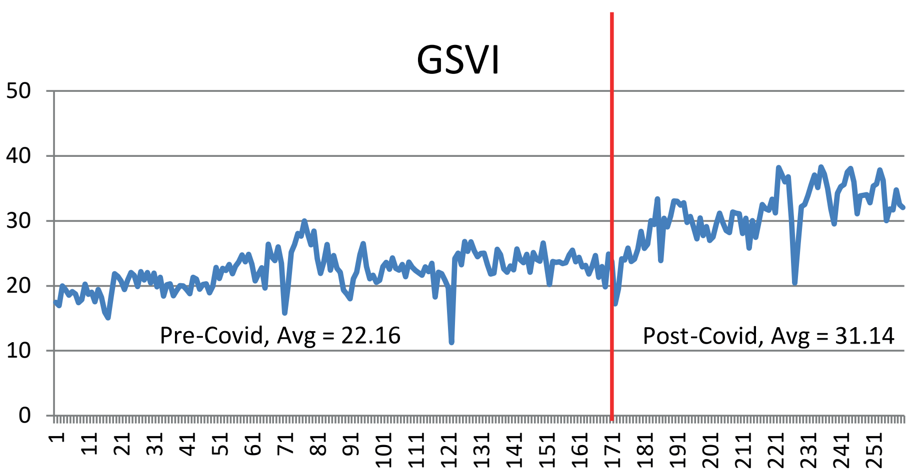

Figure 1. Variation of GSVI pre- and during-COVID-19 in Vietnam

Source: own work.

3. Results

3.1. Portfolio regressions

The models run with the portfolios are time series models. The ADF test shows that all variable series are stationary; therefore, the OLS estimation is suitable. As most models have heteroscedasticity, a robust option is included to address this issue. In most cases, the model statistics confirm the significance of the FF3FM on the Vietnamese stock market. R-squared values in the models above 0.40 in Table 2 and above 0.20 in Table 3 are low. However, these are acceptable levels with impact assessment studies. According to Ozili (2022), an R-squared between 0.10 and 0.50 is acceptable in social and economic science research only when some or most explanatory variables are statistically significant. In our paper, in the models in Table 2 and Table 3, two-thirds of the independent variables were statistically significant, thus the fitness of the models with the level of R-squared could be acceptable. Alphas in Tables 2 and 3 are intercepts of the models, presenting the risk-adjusted returns of stock portfolios. In some models, the intercepts are not significant, i.e., there is insufficient statistical evidence to assume that the constants are different from zero. However, sometimes, even if the constants are not statistically significant, it is still essential to include them in the research model for theoretical reasons and use them for analysis.

The model results for portfolios in the pre-COVID-19 period (Table 2) show a difference in the abnormal returns of different portfolios; however, there is no notable trend for all portfolios. The portfolio Q4 has a higher alpha coefficient than Q1. This implies that stocks that are searched for more often can have higher abnormal returns than those searched for less frequently.

The results for the during-COVID-19 period (Table 3) indicate a clear trend in the alpha coefficients of the four portfolios. For example, in the model with the GSVI*'s* proxy lnGSVI, the alpha coefficient for portfolio Q1 is 0.00378, Q2 is 0.00505, and Q3 is 0.00812, increasing to 0.01551 for portfolio Q4. This propensity is also true for models with other G*SVI* proxies, including ΔlnGSVI and AGSVI. As discussed in section 3.2, the Vietnamese during-COVID-19 stock market was characterized by a new wave of individual investors entering the market. From January 2020 to November 2021, 1,477,089 new accounts were opened, equivalent to nearly 74,000 new accounts per month, compared to 18,000 in the pre-COVID-19 period. Of the newly opened accounts, 99.4% were retail accounts (State Security Commission of Vietnam, 2022). Most account holders were inexperienced, lacked knowledge of stock investing, worked from home, and sought new investment channels because of social restrictions. In such instances, search engines become the primary

Table 2. Portfolio analysis of search intensity and stock returns pre-COVID-19

Variable	Intercept	Rmf	SMB	HML	R^2	Adjusted R^2	Number of observation
lnGSVI0							
Q1	0.00037	0.52147***	0.09687	0.12681	0.40127	0.39051	171
Q2	–0.00006	0.52459***	–0.14572	0.34021***	0.46100	0.45132	171
Q3	0.00007	0.61893***	–0.00828	0.36746***	0.49831	0.48930	171
Q4	0.00056	0.66200***	–0.09536	0.31121**	0.48163	0.47232	171
Q41	0.00047	0.59173***	0.00075	0.21901***	0.43618	0.43117	342
ΔlnGSVI0							
Q1	–0.00197**	0.51877***	0.04945	0.19973*	0.42742	0.41707	170
Q2	0.00054	0.62787***	–0.05201	0.25187**	0.50240	0.49341	170
Q3	0.00082	0.62574***	–0.15583	0.34479***	0.46785	0.45823	170
Q4	0.0013	0.54278***	–0.0437	0.37829***	0.40292	0.39213	170
Q41	–0.00034	0.53077***	0.00288	0.28901***	0.40732	0.40203	340
AGSVI0							
Q1	–0.00192*	0.55917***	0.03331	0.27511***	0.45825	0.44846	170
Q2	0.00075	0.62743***	0.00638	0.10152	0.50712	0.49821	170
Q3	0.00044	0.61037***	–0.14831	0.36612***	0.48583	0.47654	170
Q4	0.00136	0.51408***	–0.04929	0.43298***	0.40383	0.39306	170
Q41	–0.00028	0.53662***	–0.00799	0.35405***	0.42411	0.41897	340

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.
Note: lnGSVI0, ΔlnGSVI0, AGSVI0 are search intensity proxies with 1-period lagged variables.

Source: own work.

Table 3. Portfolio analysis of search intensity and stock returns during-COVID-19

Variable	Intercept	Rmf	SMB	HML	R^2	Adjusted R^2	Number of observation
lnGSVI(–1)							
Q1	0.00378	0.05227	–1.19392***	1.47230***	0.27831	0.25253	171
Q2	0.00504	0.06733	–1.52581***	1.58381***	0.28438	0.25882	171
Q3	0.00812**	0.07977	–1.40154***	1.52150***	0.26604	0.23983	171
Q4	0.01551***	0.06114	–1.45534***	1.62325***	0.25650	0.22994	171
Q41	0.00964***	0.05671	–1.32463***	1.54777***	0.25662	0.24365	342
ΔlnGSVI(–1)							
Q1	0.00286	0.07422	–1.24804***	1.43894***	0.25846	0.23197	170
Q2	0.00483	0.0676	–1.44522***	1.48527***	0.27622	0.25037	170
Q3	0.01146***	0.03479	–1.56697***	1.70220***	0.31879	0.29446	170
Q4	0.01323***	0.0931	–1.30411***	1.58904***	0.23426	0.20692	170
Q41	0.00805***	0.08366	–1.27607***	1.51399***	0.23815	0.22486	340
AGSVI(–1)							
Q1	0.00344	0.05352	–1.29103***	1.39546***	0.25159	0.22486	170
Q2	0.00424	0.04178	–1.44266***	1.52903***	0.26950	0.24341	170
Q3	0.00877***	0.07475	–1.45641***	1.52154***	0.27832	0.25254	170
Q4	0.01590***	0.09702	–1.37499***	1.75481***	0.28952	0.26414	170
Q41	0.00967***	0.07527	–1.33301***	1.57513***	0.25861	0.24568	340

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.
Note: lnGSVI(–1), ΔlnGSVI(–1), AGSVI(–1) are search intensity proxies with 1-period lagged variables.

Source: own work.

mode of gathering information for decision-making on various subjects, implying that search intensity has a significant effect on Vietnamese investors' trading behavior. It appears that a market with a greater number of new individual investors is less professional, and the impact of investor attention exhibited through $GSVI$ is more pronounced.

3.2. Stock-based regressions

Considering the panel dataset, we consider three models: OLS - Ordinary Least Square, FE – Fixed Effect, and RE – Random Effect models. We used the F test to decide between the OLS and FE model, with the null hypothesis of no fixed effects in stock-based models. The OLS model is selected if the p-value is greater than 5%. If it is less than 5%, rejecting the null hypothesis, we continue to perform Hausman's test to choose between the FE and RE models. After selection, most models—whether FE, RE, or OLS—have heteroscedasticity and/or autocorrelation problems. To overcome these problems, we use GLS estimation with corr(ar1) or panels(hetero) options from the Stata program.

Table 4 shows that with a no-lag search intensity, all models have good statistical indicators. The variables Rmf, SMB, and HML are statistically significant in the model at 1%. The correlation between GSVI and stock return is proven to be positive and significant. This result indicates that stocks experiencing higher search intensity undergo price increases and provide higher returns to investors. This impact is immediate, or there may be a delay of up to one week. This result is consistent with Ekinci and Bulut (2021). Comparing the estimated parameters of the GSVI variables (lnGSVI, ΔlnGSVI, and AGSVI) between the periods before and after the COVID-19 outbreak, the parameter values in the during-COVID-19 models are significantly higher than those in the pre-pandemic period. For example, the estimated impact parameter of lnGSVI to stock return is 0.00042 in the pre-COVID-19 model, while this number is 0.00225 in the during-COVID-19 model. This is consistent with the results found in the analysis of the relationship between search intensity and stock returns in the portfolio-based models in Tables 2 and 3. During the pandemic, the impact of investor attention is more robust. However, the GSVI coefficients are generally smaller than those of the other three traditional factors in the FF3FM model.

The results of the models change significantly when one-week lag GSVI variables are used. No statistically significant relationship exists between GSVI and stock returns before, during, and after the COVID-19 outbreak. This result diverges from those of Da et al. (2011), C. Nguyen et al. (2020), and C. P. Nguyen et al. (2019) but is consistent with Ekinci and Bulut (2021) and Takeda and Wakao (2014). Combined with the results of the models with no

Table 4. Stock-based analysis of search intensity and stock returns, pre- and during-COVID-19

Lag = 0	**Pre-COVID-19**			**During-COVID-19**		
Variable	**lnGSVI0**	**ΔlnGSVI0**	**AGSVI0**	**lnGSVI(–1)**	**ΔlnGSVI(–1)**	**AGSVI(–1)**
$R_m - R_f$	0.52069***	0.51956***	0.52006***	0.05525***	0.07462***	0.05692***
SMB	–0.18862***	–0.19075***	–0.19060***	–1.24598***	–1.23730***	–1.25010***
HML	0.25230***	0.25442***	0.25579***	1.23680***	1.24127***	1.23890***
GSVI0	0.00042**	0.00044***	0.00050***	0.00225***	0.00130***	0.00145***
Intercept	0	0.00107***	0.00111***	–0.0002	0.00648***	0.00679***
Number of observation	24428	24302	24302	13426	13426	13426
Lag = 1	**Pre-COVID-19**			**During–COVID–19**		
Variable	lnGSVI0	ΔlnGSVI1	AGSVI0	lnGSVI(–1)	ΔlnGSVI(–1)	AGSVI(–1)
Rmf	0.51995***	0.51919***	0.51948***	0.05557***	0.07567***	0.05530***
SMB	–0.19065***	–0.18980***	–0.18900***	–1.20297***	–1.18698***	–1.20240***
HML	0.25439***	0.25026***	0.25043***	1.20860***	1.20856***	1.20815***
GSVI(–1)	–0.00019	–0.00014	0.00001	0.00009	–0.00002	–0.00047
Intercept	0.00153***	0.00108***	0.00108***	0.00641***	0.00658***	0.00663***
Number of observation	24302	24176	24176	13276	13276	13276

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.
Note: lnGSVI0, ΔlnGSVI0, AGSVI0 and lnGSVI(–1), ΔlnGSVI(–1), AGSVI(–1) are search intensity proxies with non-lagged variables.

Source: own work.

lag SI, the results reaffirm that the impact of search intensity on stock returns occurs within one week. One possible explanation is that an increasing number of investors consider Google Search a valuable tool in their decision-making process, starting with information-seeking behavior. Consequently, the information obtained from Google searches is being incorporated into the market faster. Additionally, with the challenges faced in evaluating which individual stocks to purchase among hundreds of available stocks, investors tend to choose those that draw their attention, increasing stock prices (Odean, 1999). Therefore, in-week data can indicate the positive impact of investor attention reflected in the GSVI in stock returns.

We gradually add GSVI variable lags to the models from two-period lag onwards to identify long-term models. We denote the lagged variables as GSVI(–1) – GSVI(–9), which means the 1-to-9-period lag of the GSVI variable. The AIC and BIC statistics are employed to select the appropriate models. In principle, the smaller these values, the better the model fits the data sample. The lag of the GSVI variables selected according to the AIC and BIC statistical standards is nine. However, the model results for nine lags of GSVI variables show an unclear long-run relationship between search intensity and stock returns (Table 5). Several lag variables are statistically significant in the models using the ΔlnGSVI proxy before and after the COVID-19 outbreak. However, the lag variables are not statistically significant in most other models.

Table 6 presents the regression results when the variables SMB and HML are replaced by MK and PB, respectively, allowing for more variability in the variables for each stock included in the model. The results in Table 6 are consistent with those in Table 4, confirming search intensity's spontaneous, positive impact on stock returns. For the models with a one-week lag SI, two out of six models, i.e. the lnGSVI0 and AGSVI1 models, indicate a statistically negative impact of a one-week lag GSVI on stock returns. These models confirm the PPH and AT (Barber & Odean, 2007). Attention stimulates investors to purchase stocks, increasing stock prices; however, stock prices decrease the following week. This result is also consistent with (Bijl et al., 2016). We insist that owing to the fast flow of information on stock markets, one-week lag data only enables us to detect subsequent negative returns. The results in Table 7 are generally similar to Table 5.

Conclusions

This study examines the relationship between Google Search intensity and stock returns for stocks listed on the Vietnamese stock market. We investigated various aspects of the relationship by analysing portfolios with differ-

Table 5. Stock-based analysis of search intensity and stock returns in the long-term

	Pre-COVID-19			During-COVID-19		
Variable	**lnGSVI0**	**ΔlnGSVI0**	**AGSVI0**	**lnGSVI(–1)**	**ΔlnGSVI(–1)**	**AGSVI(–1)**
$R_m - R_f$	0.51104***	0.50990***	0.50852***	–0.03494**	–0.00952	–0.03552**
SMB	–0.19274***	–0.18024***	–0.18160***	–0.86164***	–0.83276***	–0.85909***
HML	0.25454***	0.24017***	0.24063***	1.00541***	1.00495***	1.00627***
GSVI0	0.00068***	0.00074***	0.00062***	0.00266***	0.00274***	0.00198***
GSVI(–1)	–0.00024	0.00049*	–0.00019	–0.00038	0.00232***	–0.00028
GSVI(–2)	0.00014	0.00064**	0.00026	–0.00051	0.00176***	–0.00035
GSVI(–3)	–0.00024	0.00044	0.00005	–0.00048	0.00124*	–0.0001
GSVI(–4)	0.00024	0.00071**	0.00045**	–0.00032	0.00089	0.00004
GSVI(–5)	–0.00008	0.00061*	0.00013	–0.00019	0.00064	0.00047
GSVI(–6)	0.00006	0.00068**	0.00033*	–0.00025	0.00036	0.00031
GSVI(–7)	–0.00005	0.00062*	0.00014	–0.0006	–0.00027	–0.00003
GSVI(–8)	–0.00053**	0.00013	–0.00023	–0.00024	–0.00055	–0.00012
GSVI(–9)	–0.00029	–0.00015	0.00014	0.00073*	0.00013	0.00103***
Intercept	0.00201**	0.00125***	0.00138***	0.00808***	0.00912***	0.00979***
Number of observation	23288	23162	23162	12075	12075	12075

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.
Note: lnGSVI0, ΔlnGSVI0, AGSVI0 and lnGSVI(–1), ΔlnGSVI(–1), AGSVI(–1) are search intensity proxies with non-lagged and 1-period lag variables.

Source: own work.

Table 6. Stock-based analysis of search intensity and stock returns with substituted variables

Lag = 0	**Pre-COVID-19**			**During-COVID-19**		
Variable	lnGSVI0	ΔlnGSVI0	AGSVI0	lnGSVI(–1)	ΔlnGSVI(–1)	AGSVI(–1)
$R_m - R_f$	0.55619***	0.55542***	0.54298***	0.06534***	0.06583***	0.06678***
MK	0.00123***	0.00128***	0.00130***	0.00191***	0.00226***	0.00220***
PB	–2.68872***	–2.67267***	–3.22327***	–7.90936***	–8.21793***	–8.10782***
GSVI0	0.00036*	0.00047***	0.00054**	0.00195***	0.00122***	0.00125***
Intercept	–0.03517***	–0.03573***	–0.03601***	–0.05232***	–0.05639***	–0.05459***
Number of observation	23699	23587	23587	13361	13361	13361
Lag = 1	**Pre-COVID-19**			**During–COVID–19**		
Variable	lnGSVI0	ΔlnGSVI1	AGSVI0	lnGSVI(–1)	ΔlnGSVI(–1)	AGSVI(–1)
$R_m - R_f$	0.55573***	0.55504***	0.55492***	0.06457***	0.06458***	0.06368***
MK	0.00134***	0.00127***	0.00127***	0.00250***	0.00241***	0.00245***
PB	–2.70239***	–2.69152***	–2.69124***	–8.71815***	–8.63844***	–8.71622***
GSVI(–1)	–0.00033*	–0.00017	–0.00008	–0.00049	–0.00046	–0.00081**
Intercept	–0.03657***	–0.03552***	–0.03550***	–0.06125***	–0.06022***	–0.06138***
Number of observation	23587	23475	23475	13211	13211	13211

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.
Note: lnGSVI0, ΔlnGSVI0, AGSVI0 and lnGSVI(–1), ΔlnGSVI(–1), AGSVI(–1) are search intensity proxies with non-lagged and 1-period lag variables.

Source: own work.

Table 7. Stock-based analysis of search intensity and stock returns in the long term with substituted variables

	Pre-COVID-19			During-COVID-19		
Variable	**lnGSVI0**	**ΔlnGSVI0**	**AGSVI0**	**lnGSVI(–1)**	**ΔlnGSVI(–1)**	**AGSVI(–1)**
R_{mf}	0.54767***	0.55037***	0.54934***	–0.04163***	–0.03983**	–0.04044**
MK	0.00140***	0.00130***	0.00130***	0.00310***	0.00278***	0.00275***
PB	–2.85966***	–2.86437***	–2.80484***	–1.1e+01***	–1.1e+01***	–1.1e+01***
GSVI0	0.00069***	0.00076***	0.00059***	0.00228***	0.00243***	0.00168***
GSVI(–1)	–0.00035	0.00046*	–0.00025	–0.00070*	0.00189***	–0.0006
GSVI(–2)	0.00011	0.00064**	0.00031*	–0.00025	0.00181***	–0.00006
GSVI(–3)	–0.00023	0.00047	0.00005	–0.00087**	0.00108	–0.00043
GSVI(–4)	0.00024	0.00075**	0.00043**	–0.00071*	0.00052	–0.00024
GSVI(–5)	–0.00013	0.00063*	0.00011	–0.00031	0.00035	0.0003
GSVI(–6)	–0.00001	0.00066*	0.00029	–0.00034	0.00015	0.00022
GSVI(–7)	–0.0001	0.00061*	0.00014	–0.00068	–0.00037	–0.00008
GSVI(–8)	–0.00053**	0.00014	–0.00021	–0.00066	–0.00088	–0.00043
GSVI(–9)	–0.00035*	–0.00019	0.00012	0.00048	–0.00024	0.00074**
Intercept	–0.03747***	–0.03618***	–0.03579***	–0.07027***	–0.06651***	–0.06549***
Number of observation	22691	22579	22579	12010	12010	12010

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.
Note: lnGSVI0, ΔlnGSVI0, AGSVI0 and lnGSVI(–1), ΔlnGSVI(–1), AGSVI(–1) are search intensity proxies with non-lagged and 1-period lag variables.

Source: own work.

ent search intensity levels, stock-based regressions, and models comparing small and large stocks. We used the GSVI variable with no lag and a one-week lag for short-term models and ran the long-term model with lag GSVI variables from 0 to 9 to investigate the timing of the effect. Each model is divided into two phases, before and after the COVID-19 outbreak, to simultaneously analyse and examine the relationship under different market conditions and check the robustness of models. The conclusions of this study are as follows:

First of all, the results show that GSVI positively affects stock returns in the short term. This means that the Barber and Odean's attention theory (2007) is true in the context of a frontier market. Proxied by Google Search intensity, investor attention can push investors to purchase more securities, leading to higher stock prices and returns. Moreover, the positive impact occurs within one week and reverses the following week. This result differs from most previous empirical studies, which show that the previous week's GSVI predicts the following week's stock returns (Da et al., 2011; Joseph et al., 2011; C. Nguyen et al., 2020). This result can be attributed to the fact that we used a recent dataset from 2016 to 2021. Recently, information and communication technology has penetrated and increased the speed of information on stock markets; thus, the impact of the $GSVI$ on stock returns should be faster. This also indicates that investors must react immediately to seize the opportunity of a stock price increase to make a profit.

Secondly, the search intensity impact on stock returns in Vietnam is more robust in the "during-COVID-19" period than in pre-pandemic conditions. The basic feature of Vietnam's stock market during the COVID-19 pandemic was a sharp increase in the number of first-time individual investors and online trade volume. The results suggest that when there is an event causing a sudden increase in the attention of individual investors, especially inexperienced individual investors, the impact of $GSVI$ on stock returns tends to be stronger.

Finally, the findings of this study also propose some practical implications for businesses and investors. On the one hand, the results support individual investors' use of online information, such as Google Search volume, in analysing behavioral and market trends to formulate profitable trading strategies. On the other hand, companies should focus on attracting investors' attention during share issuances. When investors pay attention to a particular stock, they Google Search more, and the stock price tends to increase.

Like other studies, this study has some limitations. First, the model is limited because GSVIs are weekly data. Therefore, it is difficult for the authors to observe accurately the day-impact and recovery period of $GSVI$'s impact on stock returns. Second, although the research has given reasons for choosing the FF3FM model, testing the data set on other models, such as CAPM, CF4, and FF5FM, will make it possible to strengthen the research results further. Finally, the study provides the GSVI impact on Vietnamese stock returns. As presented above, the Vietnamese market has all the outstanding characteristics of a frontier stock market, and the results of this research can be representative of the group of frontier markets. However, to have firm results for emerging countries, more research is required in the future for other frontier stock markets.

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