**Google Search and Stock Market Performance: Evidence from Malaysia**

Kelvin Lee Yong Ming, Universiti Malaysia Sarawak

Mohamad Jais, Universiti Malaysia Sarawak

# **Abstract**

Nowadays, the internet changes the way for information searching and processing. Along with that, Google search had become the most popular search engine on the web since it allows users access to the information at a minimal cost. This study intends to investigate the relationship between Google search volume and the Malaysian stock market performance in the aspects of returns, volatility, and trading volume. The sample of this study consisted of 29 listed companies from the Malaysian stock market. The sample period of this study covered the period from 2016 to 2018. The data related to the stock market were downloaded from Investing.com, whereas the data related to Google search were downloaded from the database of Google Trend. The results indicated that the Google search volume index (GSVI) of the previous week tends to have significant positive impacts on the stock price changes. Thus, a higher search volume of the specific company name tends to increase the stock price of the particular company in the following week. Besides that, this study also revealed that the stock market performance tends to be affected by stock market performance in the previous week. Lastly, this study suggested that signals of GSVI need to be included in the investment strategies.

Keywords: Stock Market Performance, Google Search

# **INTRODUCTION**

Stock market acts as a crucial component of the economic system and the researchers made many attempts in predicting the stock prices (Hu et al., 2018). Stock price contained the information to reflect the supply and demand of the particular stock (Torres & Hermandez-Alvarez, 2019). Specifically, Kohli et al. (2019) argued that rising stock price usually makes the investors standing out of the market and going into the market again when the stock price is declining. Nevertheless, stock market movements always react to the changes in the information (Lin et al., 2019). The flow of information also improves the market efficiency since the investor able to access the information easily once there are some changes in the macroeconomic environment (Pal and Mittal, 2011).

On the other hand, stock market movement prediction was indeed a complicated process due to the volatility of the stocks (Jin et al., 2017). Researchers also come up with different types of analysis techniques in predicting the stock prices to enable them to develop a better portfolio (Cowlessur et al., 2019). Stock market movement tends to be affected by various factors, which included macroeconomic, political and other factors (Qiu & Song, 2016). However, the efficient market hypothesis developed by Malkiel and Fama (1970) assumed that stock prices reflect all the available information in the market. Information is the most valuable asset in the financial market, not to say the stock market (Vlastakis & Markellos, 2012).

As pointed out by Dimpfl and Jank (2011), professional investors tend to monitor the stock index frequently, but not the retail investors. On the other hand, Da, Engelberg, and Gao (2009) suggested that investors’ attention also could be captured by the internet search queries. The emergence of internet search data has provided a new resource for the researcher to estimate the movements of particular data, such as macroeconomic data (Koop, 2013). Furthermore, the dramatic increase in the usage of ‘big data’ also open up the new opportunity for the researchers to further investigate the factors that affect the stock market (Preis, Moat & Stanley, 2013). Over the past two decades, investors also changed the way in obtaining information dramatically since they are able to access the information with the shortest time and lowest cost (Chi & Shanthikumar, 2017).

Before the emergence of internet, transmission of information tends to be done through billboards, televisions and word of mouth (Pai & Liu, 2018). Technological advancement also helps to connect all the people around the world and enable them to obtain information immediately (Bozanta et al., 2017). Nowadays, internet also change the way for information processing and thus changing the way how business is done (Agarwal, Kumar & Goel, 2018). In addition, internet has become a tool for the purpose of information searching since the users can access to the information at the minimal cost (Aouadi, Arouri & Teulon, 2013). In term of information searching, Google search had become the most popular search engine on the web (Bijl et al., 2016). As mentioned by

Specifically, Google Trends shows the trend in searching for the keywords and the data from Google Trends started to be applied in the field of economy (Pai, Hong & Lin, 2018).

This study aims to investigate the relationship between the google search and stock market performance in Malaysian stock market. The stock of thirty largest capitalization companies will be included for the analysis purpose. The rest of this study is organized as follows: Section 2 discusses about the related previous study. Section 3 provides the details of the data and methodology used in this study. Followed by Section 4 that discussed the empirical result obtained throughout the study. Lastly, Section 5 concludes the findings.

# **LITERATURE REVIEW**

Earlier study of Da et al. (2009) proposed direct measure the investors’ attention by using the Google search volume. of information conveyed by search volume on Google. They used the Google search volume as the proxy of investor attention since they believed that Google continued to be the search engine that widely used by internet users. Besides that, they also pointed out that 72.1 percent of all search queries in United States is done by using Google search. In addition, Bank, Larch and Peter (2011) mentioned that huge volume of available information could also be found in World Wide Web and it was accessibly by anyone, anyplace and anytime with the cost that approximates to zero.

Bank et al. (2011) investigated the relationship between the Google search volume, trading activity and stock liquidity in the Germany stock market. By using the data over the period 2004 to 2010, they found that the increase in search queries is positively associated with the trading activity and stock liquidity in Germany stock market. They also mentioned that cost of asymmetric information can be reduced with the improvement in the stock liquidity. Hence, they concluded that Google search volume able to measure the attention from uninformed investors. Moreover, they revealed that the use of strategy that combined Google search volume and market value tend to generate temporarily higher returns.

Preis et al. (2013) included 98 key terms that related to the stock market in their analysis and determine their predictive power in predicting stock market movements. Using the data spanning the period from January 2004 to February 2011, they revealed that data of Google Trend cannot be used to reflect the current situation of the stock market performance, but able to forecast the future movement of the stock market. Specifically, they found that there was increase in the volume of Google search before the stock market declining. They also further tested the ability of google search strategy, in which they taking long position when Google search volume falling and taking short position when Google search volume increase. The results obtained that google search strategy tends to generate higher return than the random investment strategy.

Bijl et al (2016) also investigate the predictive power of Google Trend in predicting the stock returns. By using the more recent data that covers the period from 2007 to 2013, they found that high volume in Google search tend to cause the stock price to deteriorate. In addition, their findings shown that trading strategy that depends on Google search volume able to generate more returns as compared to the normal trading strategy before taking any transaction costs into consideration.

Swamy and Dharani (2018) used the Google search volume index to capture the investors’ attention. They investigated the impacts of google search toward the stock returns by using the data of the companies of NIFTY 50 over the period from 2012 to 2017. They found that higher volume of Google search positively related with the stock returns. Besides that, their findings indicated that trading strategies that based on Google search volume able to generate significant returns, especially in fourth and fifth weeks.

Kim et al. (2019) investigated the ability of Google search in predict the few aspects of Norwegian stock market performance, which included the returns, trading volume and volatility. In doing so, 28 listed companies from Oslo Stock Exchange had been included in the study. Besides that, they also used the more recent data which covered the period from 2012 to 2017 in their study. They found that Google search only able to be used in predicting the volatility and trading volume, but not returns of the stock market.

Tan and Tas (2019) used Google search volume index as a proxy to measure the investor attention in Turkish stock market. Using the sample of components stocks of BIST all shares index over the period 2013 to 2017, their results shown that firms which received high attention able to generate higher return, particularly the small capitalization firms. Interestingly, they also revealed that the predictability of Google search could persisted for three weeks. By using the strategy of taking long position when there is a high attention and taking short position when there is a low attention, they found that significant returns can be achieved.

# **DATA AND METHODOLOGY**

This study intends to investigate the relationship between Google search volume and the Malaysian stock market performance in the aspects of returns, volatility and trading volume. The dependent variables used in the analysis includes the stock market performance from different aspect, such as (i) stocks return, (ii) stocks volatility and (iii) stocks trading volume. Mea in The sample of this study consisted of the 30 largest capitalization stocks which constituted the Kuala Lumpur Composite Index. The sample period used in this study covered the period from 2015 to 2018. The data related to the stock market were downloaded from Investing.com, whereas the data related to Google search were downloaded from database of Google Trend. The

**Google Search Volume Index (GSVI)**

Google search volume index has been obtained from Google Trend. GSVI measured the total search volume for a keyword, which included company names on a specific week. This study searched the company names and obtain the GSVI that related to the particular company names (Klemola, Nikkinen & Peltomaki, 2018). Meanwhile, Google trend measured the index by using the scale from 0 to 100, in which 0 represents the lowest query volume and 100 represents the high query volume related to a specific key terms (Choi & Varian, 2012). In addition, Swamy and Dharani (2018) also pointed out that GSVI would remain constant when the number of searches for the specific keyword is different from the other keywords. According to Xu et al. (2018), data of Google trend were given in four frequencies as follow:

|  |  |
| --- | --- |
| **Frequency of Data** | **Time Interval** |
| 10 min / Hourly | < 30 days |
| Daily | < 60 days |
| Weekly | < 5 years |
| Monthly | > 5 years |

**Stock Returns**

Following Kim et al. (2019), this study used the natural logarithm of the weekly stock returns as a proxy to measure the stock returns for the companies included in the analysis of this study. The calculation for the stock return of particular company is as follow:

SRx,w = log ()

where SRx,w is the stock return of company *x* at week *w*, SPw is the adjusted stock price for week *w* and SP*w-1* is the adjusted stock price from the previous week.

**Stocks Volatility**

Following Swamy and Dharani (2018), this study categorized the stock market volatility into short-term stock market volatility and long-term stock market volatility. The short-term stock market volatility is the one-week stock market volatility, whereas the long-term stock market volatility is the five-weeks stock market volatility.

Before the computation of stock market volatility, the daily stock returns are calculated as follows:

SRx,t = log ()

where SRx,t is the stock return of company *x* at day *t*, SPx,t is the adjusted stock price for day *t* and SP*t-1* is the adjusted stock price from the previous day.

The short term stock market volatility (is calculated as follows:

=

Where SRx,t = daily stock return of company x at day t

The long term stock market volatility (is calculated as follows:

= , where t = 1,2,3,4 and 5

**Stocks Trading Volume**

Following Tan and Tas (2019), abnormal turnover (or abnormal trading volume) is used as the proxy to measure the stock trading volume. The abnormal turnover is calculated as follows:

Abnormal turnoveri,t = ln (*TV*i,w) – ln [Mean(*TV*i,w-1,…, *TV*i,w-52)]

Where ln (*TV*i,t) is the natural logarithms for the trading volume of stocks *i* at week *w*, ln [Mean(*TV*i,w-1,…, *TV*i,w-52)] is the natural logarithms for the average trading volume of stocks *i* over the period from week *w-52* to week *w-1*.

**Regression analysis**

This study applied the regression analysis to investigate the impact of google search volume index (GSVI) towards the stock market returns, stock market volatility and stock market trading volume. In doing so, three models have been developed and presented as below.

**Model 1**: = + + + +

**Model 2**: = + + + +

**Model 3**: = + + + +

Where is the stock return of company *x* at week *w*, is the lagged stock return of company *x*, is the google search volume index of company *x* at week *w*, is the stock volatility of company *x* at week *w*, is the stock trading volume of company *x* at week *w*.

In addition, this study replicated the idea of Kim et al. (2019) by studying the impacts of previous information towards the future information. Thus, another three models have been developed and presented as below. Noteworthy, only the lagged variables are used as independent variables for Model 4, 5 and 6.

**Model 4**: = + + + +

**Model 5**: = + + + +

**Model 6**: = + + + +

# **RESULT AND DISCUSSION**

Table 4.1 reports the results of regression analysis for Model 1 to Model 3. The dependent variables used under Model 1, 2 and 3 were stocks returns, stocks volatility and stocks trading volume respectively. The independent variables used for Model 1 to Model 3 includes stocks return, stocks volatility, stocks trading volume and Google search. Under Model 1, only stock trading volume shown a positive and significant relationship with the stock return at the 1% level of significance. Meanwhile, stock volatility and Google search shown a negative, but not significant relationship with the stock return. Under Model 2, none of the variables shown a significant relationship with the stock volatility. Stock returns negatively related with stocks volatility, while stock trading volume and Google search positively related with stocks volatility. Similar to Model 2, the results under Model 3 shown that none of the variables shown a significant relationship with the stock trading volume. However, stock returns and stocks volatility positively related with stocks trading volume, while stock Google search negatively related with stocks trading volume. As the summary of the results from Model 1 to Model 3, the higher stocks trading volume tends to increase in the stock prices of the large capitalization stocks in Malaysian stock market.

Table 4.1 Regression Analysis (Model 1 to 3)

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Model 1** | **Model 2** | **Model 3** |
| **Dependent variable** | Return | Volatility | Volume |
| Return | - | -0.0111  (0.415) | 3.4522  (0.001) |
| Volatility | -0.0132  (0.415) | - | 0.4673  (0.678) |
| Volume | 0.0007\*\*\*  (0.001) | 0.0001  (0.678) | - |
| GSVI | -0.0002  (0.320) | 0.0002  (0.199) | -0.0044  (0.745) |
| Intercept | 0.0004  (0.153) | 0.0104\*\*\*  (0.000) | -0.2718\*\*\*  (0.000) |
| R2  Adjusted R | 0.0022  0.0138 | 0.0005  0.0001 | 0.0025  0.0019 |

Table 4.2 reports the results of regression analysis for Model 4 to Model 6. The dependent variables used under Model 4, 5 and 6 were stocks returns, stocks volatility and stocks trading volume respectively. The independent variables used for Model 4 to Model 6 includes lagged stocks return, lagged stocks volatility, lagged stocks trading volume and lagged Google search. Under Model 4, lagged stocks return shown a negative and significant relationship with the stock return at the 5% level of significance, whereas lagged Google search shown a positive and significant relationship with the stock return at the 10% level of significance. Under Model 5, only lagged stocks volatility shown a positive and significant relationship with the stock volatility at the 1% level of significance, however the other variables do not show any significant relationship with the stocks volatility. Under Model 6, both the lagged stocks volatility and lagged stocks volume shown a positive and significant relationship at the 5% and 10% level of significance respectively.

Consistently, the stock market performance in the aspect of returns, volatility and volume tend to be affected by the stock market performance in the previous week. Specifically, the increase in stocks returns in previous week tend to lower down the stocks return in the current week. On the other hand, the increase in stocks volatility in previous week tend to increase the stocks volatility in the current week. Lastly, stocks trading volume in the current week tends to be positively affected by the lagged stocks volatility and stocks trading volume. Noteworthy, the increase in the Google search for the term of a company name in the previous week tend to increase in stock prices in the current week.

Table 4.2 Regression Analysis (Model 4 to 6)

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Model 4** | **Model 5** | **Model 6** |
| **Dependent variable** | Return | Volatility | Volume |
| Lagged Return | -0.0370\*\*  (0.013) | -0.0127  (0.344) | 0.7689  (0.424) |
| Lagged Volatility | 0.0029  (0.858) | 0.1689\*\*\*  (0.000) | 2.6398\*\*  (0.012) |
| Lagged Volume | 0.0003  (0.172) | 0.0002  (0.419) | 0.3551\*\*\*  (0.000) |
| Lagged GSVI | 0.0003\*  (0.089) | 0.0002  (0.205) | -0.0180  (0.155) |
| Intercept | 0.0001  (0.795) | 0.0086\*\*\*  (0.000) | -0.1999\*\*\*  (0.000) |
| R2  Adjusted R | 0.0024  0.0015 | 0.0295  0.0287 | 0.1281  0.1273 |

**CONCLUSION**

This study investigated the relationship between Google search volume and the Malaysian stock market performance in the aspects of returns, volatility, and trading volume. The results show that current stock price changes positively affected by the Google search volume index (GSVI) from the previous week. Besides that, this study also revealed that the stock market performance tends to be affected by stock market performance in the previous week. Thus, this study suggested that signals of GSVI could be used in investment strategies.

# **References**

Aouadi, A., Arouri, M., Teulon, F. (2013). Investor Attention and Stock Market Activity: Evidence from France. *Economic Modelling*, 35, 674-681.

Agarwal, S., Kumar, S., & Goel, U. (2019). Stock market response to information diffusion through internet sources: A literature review. *International Journal of Information Management*, *45*, 118-131.

Bank, M., Larch, M., & Peter, G. (2011). Google search volume and its influence on liquidity and returns of German stocks. *Financial markets and portfolio management*, *25*(3), 239.

Bijl, L., Kringhaug, G., Molnar, P., & Sandvik, E. (2016). Google Searches and Stock Returns. *International Review of Financial Analysis*, *45*, 150-156.

Bozanta, A., Coskun, M., Kutlu, B., & Ozturan, M. (2017). Relationship between Stock Market Indices and Google Trends. *The Online Journal of Science and Technology*, *4*(7), 168-172.

Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. *Economic Record*, *88*, 2-9.

Chi, S. S., & Shanthikumar, D. M. (2016). Local bias in Google search and the market response around earnings announcements. *The Accounting Review*, *92*(4), 115-143.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461-1499.

Dimpfl, T., & Jank, S. (2016). Can internet search queries help to predict stock market volatility?. *European Financial Management*, *22*(2), 171-192.

Hu, H., Tang, L., Zhang, S., & Wang, H. (2018). Predicting the direction of stock markets using optimized neural networks with Google Trends. *Neurocomputing*, *285*, 188-195.

Hernández-Álvarez, M., Hernández, E. A. T., & Yoo, S. G. (2019, February). Stock Market Data Prediction Using Machine Learning Techniques. In *International Conference on Information Technology & Systems* (pp. 539-547). Springer, Cham.

Kim, N., Lučivjanská, K., Molnár, P., & Villa, R. (2019). Google searches and stock market activity: Evidence from Norway. *Finance Research Letters*, *28*, 208-220.

Klemola, A., Nikkinen, J., & Peltomäki, J. (2016). Changes in Investors' Market Attention and Near-Term Stock Market Returns. *Journal of Behavioral Finance*, *17*(1), 18-30.

Kohli, P. P. S., Zargar, S. Z., Arora, S., & Gupta, P. (2019). Stock Prediction Using Machine Learning Algorithms. Advances in Intelligent Systems and Computing, *698*, 405-414.

Koop, G., & Onorante, L. (2019). Macroeconomic Nowcasting Using Google Probabilities. *Topics in Identification, Limited Dependent Variables, Partial Observability, Experimentation, and Flexible Modeling: Part A Advances in Econometrics*, *40*, 17-40.

Lin, H. W., Huang, J. B., Lin, K. B., & Chen, S. H. (2019, July). Manipulated Information Dissemination and Risk-Adjusted Momentum Return in the Chinese Stock Market. In *International Conference on Applied Human Factors and Ergonomics* (pp. 37-45). Springer, Cham.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383-417.

Qiu, M., & Song, Y. (2016). Predicting the direction of stock market index movement using an optimized artificial neural network model. *PloS one*, *11*(5), e0155133.

Pal, K., & Mittal, R. (2011). Impact of Macroeconomic Indicators on Indian Capital Market. *The Journal of Risk Finance*, *12*(2), 84-97.

Pai, P. F., Hong, L. C., & Lin, K. P. (2018). Using Internet Search Trends and Historical Trading Data for Predicting Stock Markets by the Least Squares Support Vector Regression Model. *Computational intelligence and neuroscience*, *2018*.

Pai, P. F., & Liu, C. H. (2018). Predicting vehicle sales by sentiment analysis of Twitter data and stock market values. *IEEE Access*, *6*, 57655-57662.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific reports*, *3*, 1684.

Swamy, V., & Dharani, M. (2019). Investor attention using the Google search volume index–impact on stock returns. *Review of Behavioral Finance*, *11*(1), 55-69.

Tan, S. D., & Taş, O. (2019). Investor attention and stock returns: Evidence from Borsa Istanbul. *Borsa Istanbul Review*, *19*(2), 106-116.

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance*, *36*(6), 1808-1821.

Xu, Q., Bo, Z., Jiang, C., & Liu, Y. (2019). Does Google search index really help predicting stock market volatility? Evidence from a modified mixed data sampling model on volatility. *Knowledge-Based Systems*, *166*, 170-185.