RELATIONSHIP BETWEEN GOOGLE SEARCH AND THE VIETCOMBANK STOCK

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ABSTRACT

This study aims to understand the relationship between Google search and the Vietcombank stock price movement. Our weekly data consist of Google search variables and the Vietcombank variables extracted and standardized from Vietstock and Google Trend from April 2016 to April 2021. We apply the VAR Granger and Copulas approach to analyze the link between Google search and the price of Vietcombank stock. Results show that the connection between Google searches and the price of Vietcombank stock did not persist in the long run. Moreover, the evidence supporting the Granger causality between Google searches and the Vietcombank stock price was weak. Finally, the trading name (term "Vietcombank") was preferred by Google search users over the code "VCB," and the trading volume and Google search simultaneously increased within the sample period.

Keywords: Google Search, Vietcombank, Copula, VAR Granger

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INTRODUCTION

The prediction of stock returns is an interesting subject in the finance domain. In practice, stock price movements can be predicted using technical analysis tools integrated on most stock websites. Accordingly, existing publications have explored various approaches and factors of stock movements. Besides the conventional stock factors (e.g., financial indicators and macroeconomic factors), Coyne et al. (2017) showed that StockTwits on social media might predict stock price movement with an accuracy of approximately 65%. Kim and Kim (2019) proposed the feature fusion long short-term memory-convolutional neural network model to forecast stock movement.

Efficient market theory indicates a significant relationship between information and stock prices (Fama et al., 1969). With considerable knowledge available on the Internet, searching keywords via Google is a popular choice in the current digital era. On the basis of the searched keyword volume recorded by the Google Trend tool within their study period, Bijl et al. (2016) and Nguyen et al. (2019) implied that Google searches negatively affect stock returns. In contrast, Ekinci and Bulut (2021) and Swamy and Dharani (2019) argued that the relationship between Google searches and stock returns is positive. Therefore, Google search can predict stock price movements, although the empirical results are not consistent. Following the existing studies, we aim to conduct empirical research to test the relationship between Google search and specific stock prices. We consider that our results will be meaningful for investors holding or intend to have any particular stock.

In this study, we select the stock of Vietcombank, which is listed on the Ho Chi Minh Stock Exchange Market in Vietnam. Vietcombank is the biggest bank by capitalization in Vietnam, one of the biggest banks in issuing credit and providing retail products and is adapting to digitalization. The information about Vietcombank is of great significance for investors and Internet users. Thus, we argue that selecting Vietcombank is appropriate for testing the relationship between Google search and stock movement.

LITERATURE REVIEW

In recent years, the relationship between Google searches and stock returns has attracted the attention of many scholars. In this section, we review few prior empirical studies as our theoretical framework.

We found that Google search has been used as the influencing variable on other financial issues. For example, Kim et al. (2019) investigated the effect of Google search on stock market activity in Norway. Bank et al. (2011) showed that the effects of Google search helped increase trading activities and stock liquidity in Germany. Nasir et al. (2019) used Google search to predict the movement of Bitcoin. Salisu and Vo (2020) indicated that the searching volume of the keyword “health news” on Google Trend is a significant factor, which is used to predict stock returns in the COVID-19 pandemic. In addition, Desagre and D’Hondt (2021) found a significant relationship between Google search volume and retail trading activity.

Regarding the relationship between Google search and stock returns, we selected the high-quality articles of Bijl et al. (2016), Nguyen et al. (2019), Ekinci and Bulut (2021), and Swamy and Dharani (2019). Bijl et al. (2016) collected weekly data of listed companies in the S&P 500 and the search volume of company names from Google Trends from 2007 to 2013 to investigate the relationship between Google searches and stock returns. They found that Google search volume predicts the stock return but changes over time. Specifically, the high Google search volume is optimistic with the return at the first and second weeks but will eventually turn negative. Accordingly, they provided the appropriation of weekly data’s role in the finance market concerning the information in the digital world.

Next, on the basis of panel data from 1729 listed companies in the Southeast Asia region (Indonesia, Malaysia, Philippines, Thailand, and Vietnam) and Google search volume from 2009 to 2016, Nguyen et al. (2019) developed the Fama–French model to estimate the effect of Google search volume on stock returns. In Vietnam, the Philippines, and Thailand, the lower stock returns are significant with higher Google search volume. However, no evidence showed whether Google search volume has a significant relationship with stock returns in Indonesia and Malaysia.

Ekinci and Bulut (2021) collected weekly data on BIST 100 stocks and Google Trends from 2012 to 2017 to investigate the relationship between Google search and stock at Borsa Istanbul. Using the Fama–French three-factor model and stock-level regressions, they explored whether a link exists between Google search and stocks. Although their results showed that the positive returns are highly linked to search volume, they did not pursue it any further. Instead, they performed stock-level regressions throughout stock categorization. Overall, the link between Google search and stock returns is significant in the small-cap stocks, sports, and real estate industries.

Finally, following the study by Bijl et al. (2016), Swamy and Dharani (2019) investigated the effect of Google search on the stock trading behavior of the NIFTY 50 in the India Stock Exchange market from July 2012 to June 2017. They combined their time-series data (stock-level regression) with their panel data using an estimation procedure. Their main finding confirmed that Google search significantly positively affects stock movements. Moreover, domestic investors were more sensitive with Google search than worldwide investors. On this basis, they concluded that the Google search movement is a significant signal, which might affect investors' trading behavior. It is consistent with the finding of Sanchez (2021), that there is a significant impact of Google search volume on the trading volume volatility of 50 firms on the EURO STOXX-50 by the asset pricing model estimation.

The volume of Google searches reflects the behavior of Internet users in searching keywords. Accordingly, this study aims to explore the link between Google search and stock price movement. Specifically, we hypothesize that the research issue follows efficient market theory. Fama et al. (1969) and Fama and French (1997) identified three forms of market efficiency: weak form, semi-strong form, and strong form, categorized by the effect of information on the movement of stock price. The weak form is often observed in emerging markets, such as the Vietnamese stock market (Truong et al., 2010; Vo & Truong, 2018). Thus, the stock price does not depend on the information disclosed at the present and the future. Instead, we argue that the Google search might not affect Vietcombank's stock price movement.

In general, Google searches on stock price movement have a significant effect. We use efficient market theory to explain such a relationship. In the case of Vietcombank stock, the weak form will be more meaningful than other forms under efficient market theory.

METHODOLOGY

Variable measurement and data collection

Following Bijl et al. (2016), Swamy and Dharani (2019), and Ekinci and Bulut (2021), we collected weekly data for the analysis. Weekly data are appropriate for our study because they have been available for several years, are not disrupted by the holidays, and match the raw data from Google Trends.

We derived the stock price of Vietcombank from Vietstock and the Google search volume from Google Trends. On the basis of the collected data, we measured the variables of Google search and Vietcombank stock price in the following subsections.

Google search variables

Google Trends provides the Google search volume of specific keywords for a period of time. It offers hourly and weekly data for the short and long term, respectively. The Google search volume interval (GSVI) is from 0 to 100, which shows the volume of searching keywords from the lowest to the highest.

The suitable keywords play a critical role in extracting data from Google Trends. Following Ekinci and Bulut (2021), Nguyen et al. (2019), and Bijl et al. (2016), we selected the stock ticker symbol of Vietcombank (code: VCB) for extracting the data. Bank et al. (2011) determined a significant relationship between brand name and returns. Thus, we also selected the brand name of Vietcombank, i.e., "Vietcombank." We also used the Vietnamese terms for Vietcombank (e.g., "ngân hàng ngoại thương," "ngân hàng thương mại cổ phần ngoại thương Việt Nam," and "NHTMCP Ngoại thương") to extract the data. Given their extremely low volume, however, we decided not to consider them in the analysis.

The value of using raw searching volume keywords depends on the period of downloaded data. Accordingly, Kim et al. (2019), Huynh (2019), and Bijl et al. (2016) proposed the following measurement of GSVI:

$$GSVI_t = \frac{GSV_t - \frac{1}{52}\sum_{i=1}^{52} GSV_{t-i}}{\sigma_{GSV,t}}, \quad (1)$$

GSV has a value from 0 to 100, indicating the search keywords on Google in a week.

Nguyen et al. (2019) used logarithms of Google search volume to measure the Google search variables. Thus, we also used this measurement for computing the Google search variables in our analysis.

In this study, the Google search variables Log-VCB and Log-Vietcombank denote the logarithm of GSV of the terms “VCB” and “Vietcombank,” respectively. Then, we measured GSVI-VCB and GSVI-Vietcombank using Equation (1).

Vietcombank stock return variables

Following Swamy and Dharani (2019) and Bijl et al. (2016), we selected the first opening price of a week to measure the stock return because it reflects the rational reaction of investors after the release of the week of the Google search keywords (reported at the weekend).

We also referred to Kim et al. (2019), Kiymaz and Berument (2003), Truong et al. (2020), and Nguyen et al. (2019) to calculate the Vietcombank stock return as follows:

$$RVCB_t = log(P_t) - log(P_{t-1}) = log\frac{P_t}{P_{t-1}} \quad (2)$$

where RVCBt is the Vietcombank stock return at week t. Pt and Pt−1 are the first opening prices of week t and week t−1, respectively.

Following Swamy and Dharani (2019) and Bijl et al. (2016), we calculated the weekly short-term volatility of Vietcombank stock return (Vo-short) as follows:

$$Vo - short_t = \sqrt{\sum_{i=1}^{n} r_i^2}, \quad (3)$$

where n is the number of trading dates during the corresponding week. r is the daily returns measured similar to Equation (2).

On the basis of the average of weekly short-term volatilities for the last five weeks, we calculated the weekly long-term volatility (Vo-long) as follows:

$$Vo - long_t = \frac{1}{5}\sum_{t=-4}^{0} Vo - short_t. \quad (4)$$

On the basis of the trading volume during a week (Swamy and Dharani, 2019; Bijl et al., 2016), we calculated the weekly trading volume variable (Vol) as follows:

$$Vol_t = \log(volume_t) - \frac{1}{12}\sum_{i=-12}^{-1} log(Volume_i) \quad (5)$$

Accordingly, the Vietcombank stock variables consist of Vietcombank stock return (RVCB), Vietcombank stock volatility (Vo-short and Vo-long), and the trading volume of Vietcombank stock (Vol).

Model

To test the relationship between Google search and the Vietcombank stock returns, we referred to applying vector autoregression (VAR) and Granger causality for time-series estimation. However, to ensure that the estimation results are reliable, we also conducted a prior descriptive statistical analysis, unit root test, optimal lags, and co-integration test. All estimation results are discussed in the next section.

The function expresses the relationship between Google search and Vietcombank as follows:

Vietcombank stock = f(Google search). (6)

In accordance with the determined variables above, the specific functions of Google search and Vietcombank are as follows:

- Model 1: RVCB = f(Log-VCB, Log-Vietcombank), (7)
- Model 2: RVCB = f(GSVI-VCB, GSVI-Vietcombank), (8)
- Model 3: Vo-short = f(Log-VCB, Log-Vietcombank), (9)
- Model 4: Vo-short = f(GSVI-VCB, GSVI-Vietcombank), (10)
- Model 5: Vo-long = f(Log-VCB, Log-Vietcombank), (11)
- Model 6: Vo-long = f(GSVI-VCB, GSVI-Vietcombank), (12)
- Model 7: Vol = f(Log-VCB, Log-Vietcombank), (13)
- Model 8: Vol = f(GSVI-VCB, GSVI-Vietcombank). (14)

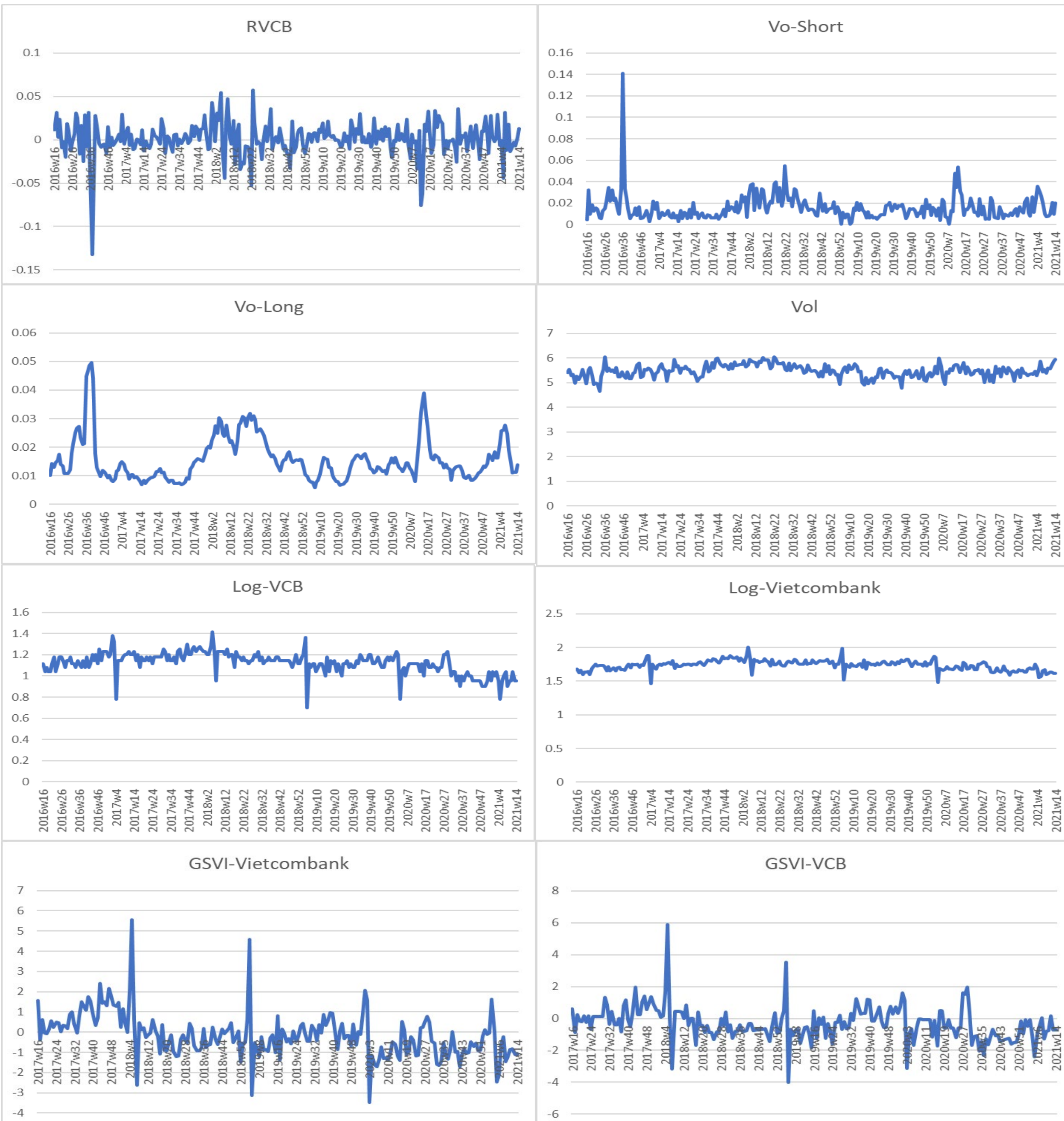
Following Huynh et al. (2018), Nasir et al. (2019), and Huynh et al. (2020), we applied the Copula approach for the robustness check concerning the relationship between Google search and Vietcombank stock returns. First, the results of the Kendall plot are the graphics used to diagnose the dependence structure between variables. Second, using the diagnostics with graphics, we applied Clayton, Gumbel, and

Normal Copulas to estimate the left-tail, right-tail, and non-tail dependency between variables, respectively.

Data

We collected the raw data from Vietstock and Google Trends from April 2015 to April 2021 and computed the variables using the equations provided above. Equation (1) requires the 52 previous weekly data from April 2016 to April 2021 for the analysis. Finally, given the requirement of the Copula approach, we standardized the required data in the interval of [0, 1].

RESULT AND DISCUSSION



Descriptive statistics

Table 1 shows the statistical description. We analyzed the indicated values to gain insight into the data feature.

Table 1. The statistical description of the study variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
RVCB	261	0.0014304	0.0193619	−0.1324483	0.0569049
Vo-short	261	0.0158034	0.0119488	0.0006870	0.1407682
Vo-long	261	0.0157606	0.0077251	0.0058976	0.0496104
Vol	261	5.4698390	0.2539414	4.6399350	6.0427810
Log-VCB	261	1.1226690	0.0993955	0.6989700	1.4149730
Log-Vietcombank	261	1.7372600	0.0731560	1.4623980	2
GSVI-VCB	209	−0.2913086	1.0299350	−4.018861	5.865363
GSVI-Vietcombank	209	−0.1411292	1.0679140	−3.471572	5.557674

Source: The Authors

Most variables had 261 observations, except for GSVI-VCB and GSVI-Vietcombank, which only had 209 observations caused by the dropout of 52 weekly observations following Equation 1.

The short-term volatility of Vietcombank's stock return was higher than its long-term volatility (Vo-shortmean > Vo-longmean, and Vo-shortStd.Dev. > Vo-longStd.Dev.). The term "Vietcombank" was also more preferred than the term "VCB" by Google search users (Log-Vietcombankmean > Log-VCBmean, and GSVI-Vietcombankmean > GSVI-VCBmean).

Unit root test

We used the Dickey–Fuller and Phillips–Perrons approaches to check the stationary of data series or unit root test. Table 2 shows the estimation results of the unit root test.

Table 2. Estimation results of the unit root test

Variable	Dickey–Fuller		Phillips–Perron	
	t-statistic	Stationary	t-statistic	Stationary
RVCB	−14.310***	Yes	−14.243***	Yes
Vo-short	−10.679***	Yes	−10.858***	Yes
Vo-long	−3.380**	Yes	−4.157***	Yes
Vol	−8.519***	Yes	−8.632***	Yes
Log-VCB	−8.844***	Yes	−9.031***	Yes
Log-Vietcombank	−8.864***	Yes	−9.004***	Yes
GSVI-VCB	−10.195***	Yes	−10.401***	Yes
GSVI-Vietcombank	−9.190***	Yes	−9.370***	Yes

Note: *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.
Source: The Authors

The estimation results by the Dickey–Fuller and Phillips–Perron approaches were consistent. All data series were stationary at the 1% confidence level, except for Vo-long, which was stationary at the 5% significant level. Thus, we did not use the alternative specification of variables (i.e., first difference) for the unit root test. Instead, we employed the data series at level I(0) for further quantitative analysis.

Choosing the optimal lags

Next, we chose the optimal lags. This stage is crucial to the processing data series. Following the approach introduced by Lütkepohl (2005), we provided the central statistics (FPE, AIC, HQIC, and SBIC) in Table 3.

Table 3. The lag-order selection

	Model 1				Model 2			
Lag	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	5.9e-09	−10.44050	−10.42380	−10.39910	2.3e-09	−11.37390	−11.35730	−11.33250
1	3.3e-09	−11.01140	−10.94480	−10.84570*	1.1e-09	−12.10670	−12.04000	−11.94090*
2	3.0e-09	−11.12590	−11.00930*	−10.83590	9.9e-10	−12.22090	−12.10430*	−11.93090
3	2.9e-09	−11.16060	−10.99400	−10.74630	9.5e-10	−12.25770	−12.09110	−11.84340
4	2.8e-09*	−11.18400*	−10.96740	−10.64540	9.2e-10*	−12.29800*	−12.08140	−11.75940
	Model 3				Model 4			
Lag	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	9.7e-10	−12.2436	−12.2269	−12.2022	1.0e-06	−5.28661	−5.26995	−5.24518
1	8.8e-11	−14.6405	−14.5738	−14.4748	4.1e-07	−6.18872	−6.12208	−6.02300
2	7.1e-11	−14.8600	−14.7434*	−14.5700*	3.6e-07	−6.32224	−6.20562	−6.03224*
3	6.7e-11	−14.9060	−14.7394	−14.4917	3.4e-07	−6.38963	−6.22303*	−5.97535
4	6.6e-11*	−14.9330*	−14.7164	−14.3944	3.3e-07*	−6.40580*	−6.18921	−5.86722
	Model 5				Model 6			
Lag	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	0.000129	−0.445026	−0.425356	−0.396396	0.000035	−1.73766	−1.71799	−1.68903
1	0.000097*	−0.731098*	−0.652420*	−0.536580*	0.00002	−2.28557	−2.20689*	−2.09105*
2	0.000100	−0.692588	−0.554902	−0.352182	0.00002*	−2.29697*	−2.15928	−1.95656
3	0.000101	−0.688178	−0.491484	−0.201884	0.00002	−2.28601	−2.08932	−1.79972
4	0.000104	−0.661408	−0.405705	−0.029225	0.00002	−2.28223	−2.02652	−1.65004
	Model 7				Model 8			
Lag	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	0.000018	−2.41226	−2.39259	−2.36363	0.02564	4.85004	4.86971	4.89867
1	1.6e-06	−4.83675	−4.75808	−4.64224*	0.013432	4.20349	4.28217*	4.39801*
2	1.5e-06	−4.91620	−4.77851*	−4.57579	0.012993	4.17018	4.30786	4.51058
3	1.4e-06	−4.93818	−4.74149	−4.45189	0.012436*	4.12626*	4.32295	4.61255
4	1.4e-06*	−4.94377*	−4.68807	−4.31159	0.012775	4.15282	4.40853	4.78500

Note: * is the suggestion of lag-order selection
Source: The Authors

According to Ivanov and Killian (2001), Nasir et al. (2019), and Huynh (2019), the AIC (Akaike's Information Criterion) is appropriate to consider for choosing the optimal lags of weekly data series as in this study. Therefore, we applied it as follows: the optimal lags of four (4) for Models 1, 2, 3, 4, and 7, lags of one (1) for Model 5, lags of two (2) for Model 6, and lags of three (3) for Model 8.

Co-integration test

Given the selected lags above, we conducted a co-integration test for our eight models using the vector error-correction model (Lütkepohl, 2005; Johansen, 1988; Nasir et al., 2019; Huynh, 2019). Table 4 shows the estimation results.

Table 4. Estimation results of the co-integration test

	Model 1				Model 2			
Rank	LL	Eigenvalue	Trace Statistic	5% critical value	LL	Eigenvalue	Trace Statistic	5% critical value
0	1430.2910		91.7030	29.68	1586.2287		66.1211	29.68
1	1461.4027	0.21503	29.4796	15.41	1605.6972	0.14059	27.1841	15.41
2	1471.6808	0.07687	8.9234	3.76	1614.9525	0.06949	8.6735	3.76
3	1476.1425	0.03413			1619.2893	0.03319		
	Model 3				Model 4			
Rank	LL	Eigenvalue	Trace Statistic	5% critical value	LL	Eigenvalue	Trace Statistic	5% critical value
0	1932.0955		51.5947	29.68	836.61813		51.0536	29.68
1	1945.0346	0.09579	25.7165	15.41	847.87094	0.08385	28.5480	15.41
2	1953.8519	0.06632	8.0819	3.76	857.79249	0.07431	8.7049	3.76
3	1957.8929	0.03096			862.14494	0.03330		
	Model 5				Model 6			
Rank	LL	Eigenvalue	Trace Statistic	5% critical value	LL	Eigenvalue	Trace Statistic	5% critical value
0	−56.392025		295.2060	29.68	197.62632		127.8358	29.68
1	13.592420	0.48979	155.2371	15.41	225.82690	0.23850	71.4346	15.41
2	58.563867	0.35106	65.2942	3.76	246.89153	0.18415	29.3054	3.76
3	91.210961	0.26942			261.54422	0.13201		
	Model 7				Model 8			
Rank	LL	Eigenvalue	Trace Statistic	5% critical value	LL	Eigenvalue	Trace Statistic	5% critical value
0	514.64530		62.1828	29.68	−432.22522		77.1731	29.68
1	531.48229	0.15148	28.5088	15.41	−414.00777	0.16211	40.7382	15.41
2	539.77323	0.07770	11.9270	3.76	−401.73777	0.11230	16.1982	3.76
3	545.73671	0.05652			−393.63866	0.07562		

Source: The Authors

Table 4 shows no co-integrating relationship between Google searches and Vietcombank stock variables, expressing the relationship between the variables in our eight models (e.g., RVCB and Logarithm of Google searches and volatility and Google search). Such pairs of variables did not persist in the long run. Therefore, we deemed the VAR estimation as appropriate to use for the assessment of the relationship between Google searches and Vietcombank stock.

Granger causality estimation

Following Nasir et al. (2019) and Huynh (2019), we applied the VAR Granger to understand the causal relationship between Google search and Vietcombank stock returns. Table 5 shows the estimation results.

Table 5 shows no evidence of bi-directional causality between pair variables, i.e., Google searches and Vietcombank stock returns. However, we found that the uni-directional causality of some pair variables was significant at the 10% level. These pair variables are as follows: from Log-VCB to Vo-short and from GSVI-Vietcombank to RVCB (or from Google search to Vietcombank stock); from Vo-long to Log-VCB, from Vo-short to GSVI-Vietcombank, and from Vol to GSVI-Vietcombank (or from Vietcombank stock to Google searches); and from Log-VCB to Log-Vietcombank and GSVI-VCB to GSVI-

Vietcombank (or from Google searches to Google searches).

Table 5. Granger causality for variables

Panel 1	RVCB	Log-VCB	Log-Vietcombank	All
RVCB	—	4.4600	7.3271	9.3664
Log-VCB	3.7960	—	6.3401	10.6370
Log-Vietcombank	4.1274	4.4061	—	8.5801
Panel 2	Vo-short	Log-VCB	Log-Vietcombank	All
Vo-short	—	3.5178	3.1615	6.0368
Log-VCB	9.1590*	—	7.0461	16.1410**
Log-Vietcombank	5.3458	4.8086	—	9.8193
Panel 3	Vo-long	Log-VCB	Log-Vietcombank	All
Vo-long	—	8.0503*	4.9455	10.7710
Log-VCB	2.1782	—	6.3950	8.9773
Log-Vietcombank	1.9702	4.3931	—	6.3861
Panel 4	Vol	Log-VCB	Log-Vietcombank	All
Vol	—	4.8363	6.5776	13.4630*
Log-VCB	4.9172	—	7.7801*	11.7880
Log-Vietcombank	1.9131	4.2976	—	6.3280
Panel 5	RVCB	GSVI-VCB	GSVI-Vietcombank	All
RVCB	—	0.89227	1.0783	1.1076
GSVI-VCB	1.4546	—	4.3e-05	1.4765
GSVI-Vietcombank	2.7949*	0.08666	—	2.9088
Panel 6	Vo-short	GSVI-VCB	GSVI-Vietcombank	All
Vo-short	—	2.7135	5.25430*	6.0031
GSVI-VCB	3.1224	—	0.04659	3.1965
GSVI-Vietcombank	2.0961	0.1024	—	2.1809
Panel 7	Vo-long	GSVI-VCB	GSVI-Vietcombank	All
Vo-long	—	7.0058	1.8815	15.1110*
GSVI-VCB	1.2559	—	7.6199	8.9510
GSVI-Vietcombank	1.3084	2.7569	—	4.3387
Panel 8	Vol	GSVI-VCB	GSVI-Vietcombank	All
Vol	—	3.2541	7.6997*	9.5659
GSVI-VCB	5.1378	—	6.5971*	11.7300*
GSVI-Vietcombank	2.0438	3.5814	—	5.7196

Note: *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.
The null hypothesis is that the variable in the row is not a Granger cause variable in the column.
Source: The Authors

Thus, we argued that the evidence of Granger causality between Google searches and Vietcombank stock returns was weak. We also determined that searching the term "Vietcombank" was more of an effect of the change of Vietcombank stock returns than the term "VCB," and the volume of searching the term "Vietcombank" was caused by the term "VCB." This finding was consistent with our previous one that "Vietcombank" was a more favorable trading name.

Copula estimation

Following Trivedi and Zimmer (2007), Hasebe (2013), and Nasir et al. (2019), in this study, we employed the Copulas approach to estimate the dependency structure between Google searches and Vietcombank stock returns. We used Copulas to enrich our estimate given (1) our inclusive empirical study and (2) the extremely rigid assumptions of the previous test. Copulas meets more criteria for evaluating dependency structures, such as left-tailed, right-tailed, or normal distributions. In addition, the Copulas approach is the better predictor for determining tail dependency rather than structure. However, the non-parametric method is suitable for estimating the dependence structure for a pair of random variables. Accordingly, we used the Copulas approach to assess the dependency relationship by joining the marginal distribution with the joint distribution of the variables being evaluated. The proposed method is better than using correlation or causality, which has the drawback of scalar measures of dependence or linear estimations.

Kendall-plot graphics

The Kendall-plot or K-plot shows the graphic, which illustrates the inter-relationship between two variables: VCB stock and Google searches. The pair variables have a structural dependence if the defined points do not lie on the 45-degree line of the graph.

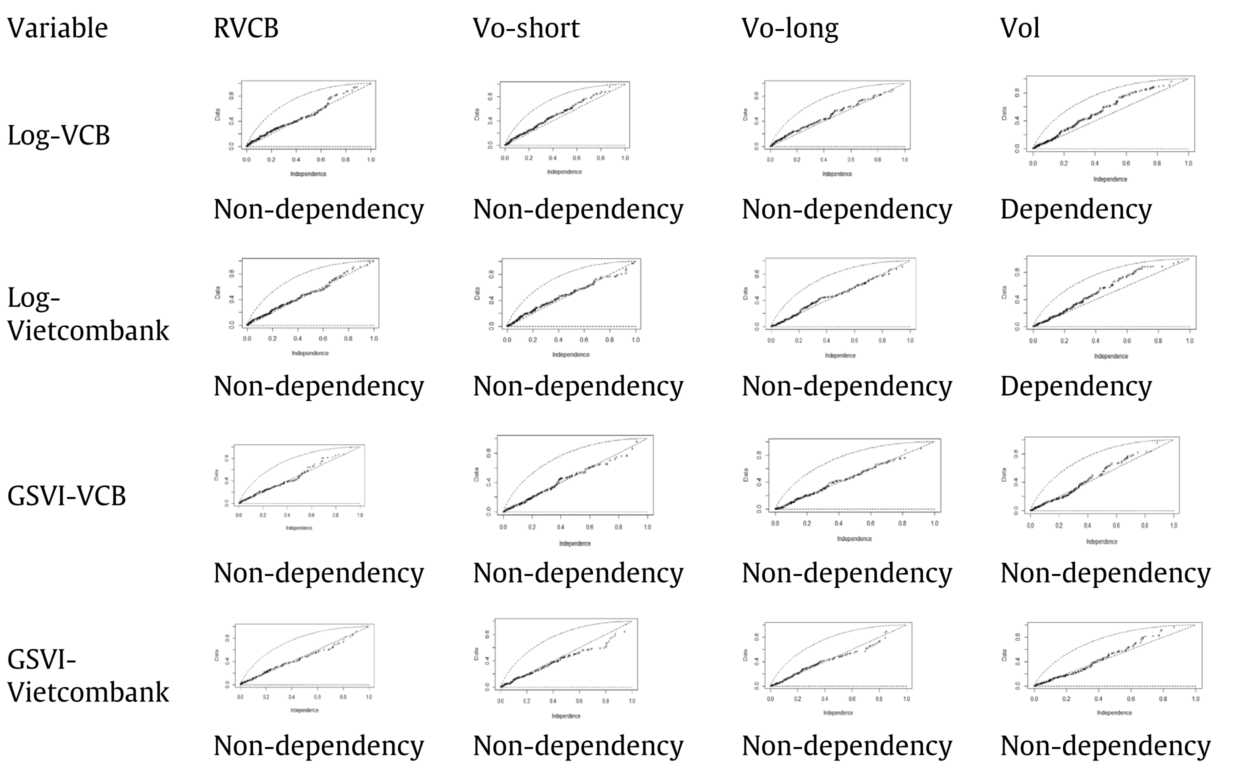


Figure 1. Kendall-plot graphics illustrating the dependency structure among pair variables
Source: The Authors

Figure 1 shows that most pairs of variables between VCB stock and Google searches were non-dependency, except for the pairs of Vol and Log-VCB and Vol and Log-Vietcombank. However, Huynh et al. (2020) stated that the Kendall-plot only provides a graphical diagnosis of the random and continuous variables. This method does not provide insights into structural dependency, namely, the interconnected tail between variables. Therefore, we conducted further investigation.

Parameter estimates

On the basis of the structural dependency between pair variables (Vol and Log-VCB and Vol and Log-Vietcombank), we employed the Copulas approach to continue the robustness check.

The three families of Copulas are Gumbel, Clayton, and Normal (Gaussian), which are famous in the finance field (Huynh et al., 2020). Given the scope of our study, we used Gumbel, Clayton, and Normal to determine the tail-dependency of pair variables. The Gumbel Copula captured the upper tail dependence or right tail, indicating that two events might incur simultaneously in the positive case. The Clayton Copula showed the lower tail or left tail, and in the negative case, the two events might incur simultaneously. Finally, the Normal Copula showed no tail structural dependence between two variables.

We also employed the maximum pseudo-likelihood method to estimate the parameters of the Copulas of Gumbel, Clayton, and Normal. In selecting the fittest estimation result between the three families of Copulas, we considered the highest value of log-likelihood (Huynh et al., 2020).

Table 6. Estimated parameter results by the three copula approaches

		Vol and Log-VCB	Vol and Log-Vietcombank
Clayton	Parameter	0.234	0.287
	Loglikelihood	3.566	3.682
Gumbel	Parameter	1.153*	1.174*
	Loglikelihood	5.812	7.544
Normal	Parameter	0.1995	0.2096
	Loglikelihood	4.9350	5.4620

Note: (*) is the fittest estimation.
Source: The Authors

Table 6 indicates a right-tail dependency (Gumbel Copula) on Volume and Google search. Specifically, the simultaneous increase of trading volume and Google searches were high, consistent with Ekinci and Bulut (2021) and Swamy and Dharani (2019).

Thus, the estimation results between the two approaches for evaluating the link between Google search and Vietcombank stock returns were not consistent. The VAR Granger is considered the conventional approach of estimating the relationship between time-series variables, and the Copula approach is the emerging approach in the finance field. We argued that the estimation results of the two methods did not provide significant convincing evidence to conclude the relationship between Google search and Vietcombank stock returns. The reason behind such a conclusion might be the weak-form efficiency of the Vietnamese stock exchange market (Truong et al., 2010) and the weak link between the information and the return of Vietcombank stock. Overall, the Google search did not influence Vietcombank stock movement in this study.

CONCLUSION

The behavior and dynamics of stock returns are the prime interest to investors and scholars. In the current digital era, Google is a critical tool to search for information before making investment decisions among investors. Using the Google search volume to predict the stock movement of stock returns has attracted adequate attention from scholars. We chose one of the biggest commercial banks in Vietnam to investigate the link between Google search and its stock returns, given that the Vietcombank stock is always attractive in the Vietnam stock exchange market. We extracted our weekly data from Vietstock and Google Trends and conducted our analysis. First, we employed the VAR framework to estimate the link between Google search and the return on Vietcombank stock. Second, we applied the Copula approach as the robustness checking method. The estimation results showed that (1) there is no evidence to conclude the persistence of Google searches and the return on Vietcombank stock in the long run; (2) the evidence of Granger causality between Google searches and Vietcombank stock returns was weak.; (3) the trading name (the term "Vietcombank") was more preferred by Google search users than the code "VCB"; and (4) the trading volume and Google search exhibited a simultaneous increase in the same period.

This study generally contributes to the literature on using Google search to predict stock price movement. Besides that, the study also contributes to the application of the Google search, VAR framework, and Copulas approach for trading the specific stock in an emerging country, where market efficiency is weak. We consider that it is a significant contribution, is caused by the high-practice, and is a significant reference that is meaningful for investors in the digital era.

On the basis of the above findings, we suggest some implications for relevant entities. First, the investors who always attend stock price movement must focus on the simultaneous increase of Google search and trading volume. Following the conclusion of Swamy and Dharani (2019) about the effect of Google search on investors' trading behavior, we also recommend that it might be the signal of positive change of Vietcombank stock price movement. Accordingly, investors might make purchase or sell decision. Second, the board management of Vietcombank should prioritize using the term "Vietcombank" in advertising campaigns, given that it is more preferred by Internet users than the term "VCB," especially in disclosing positive information. Third, stock consultant organizations might apply the method as well as a result for the consulting process. We believe that these will be the adequate ways to adapt to changes in the digital world.

The weak evidence of the link between Google search and the Vietcombank stock return might be an effect of the weak-form of market efficiency in Vietnam. Therefore, we propose that follow-up studies should consider other factors, which are not mentioned in this research, to investigate the movement of Vietcombank stock returns. Besides the application of Kendall-plot and the three families of Copulas (Normal, Clayton, and Gumbel), the Copulas approach has other relevant branches, such as Chi-plot, Frank, and Plackett. They can be used to estimate the structural dependency between Google search and stock price movement or other financial assets. Fellow researchers may also apply the rest of the Copula branches and extend the scope of this study in the future (e.g., extend the scope of time and or intention of searching Vietcombank outside Vietnam of international investors).

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