Do Fintech-Related Keywords Influence Bank Return? A Case Study from Vietcombank and Sacombank in Vietnam

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Abstract

The study is conducted to answer the question 'Do fintech-related keywords on searching Google influence bank return?' The weekly data from 2016w1 to 2021w2 is extracted from Google Trends and the Vietstock website. The findings by VAR (Vector Autoregression) show no evidence of the association of fintech-related keywords with bank returns. Using OLS (Ordinary Least Squares), the Vietcombank return is not significantly influenced by the fintech-related keywords. In contrast, the term "financial technology" and the lag one week of the Vietnamese form of "mobile payment" are negatively significant with the Sacombank return, and the Vietnamese form of "peer-to-peer lendings" is significantly positive with the same. Moreover, the fintech-related keywords in English are more preferred than the Vietnamese forms.

Keywords: *Fintech-related keywords, Google Trends, Bank Return, Vietnam*

1. Introduction

The term “fintech” is the buzzword derived from the combination of the words “financial” and “technology.” Fintech is used to indicate disruptive technologies in the finance sector, especially in commercial banks. Therefore, there is a strong link between fintech and banks(Lee & Shin, 2018; Goldstein et al., 2019; Thakor, 2020; Cheng & Qu, 2020). Moreover, by collecting fintech-related keywords on the internet, Cheng and Qu (2020) and Wang et al. (2021) investigated the influence of fintech information flow on the bank. Therefore, we consider that the volume of searching “fintech” on the internet might influence the bank.

Google Search Engine (called Google) is the most popular tool to find out information by searching keywords. Investigation of the impact of searching keywords on the various socio-economic aspects has attracted many scholars. Huynh (2019) evaluated the influence of keywords on entrepreneurs (measured by the number of new businesses and the amount of cash spent in registration). Nasir et al. (2019) discovered that keywords had a beneficial effect on Bitcoin return and trading volume. Bijl et al. (2016) investigated the inverse association between keywords and stock return volume. In Vietnam, Thailand, and Philippines, Nguyen et al. (2019) found that the increase of keywords is negative with stock return. Besides that, Kim et al. (2019) found that the searching keyword on Google can predict stock volatility and trading volume. Therefore, we argue that there is a significant impact of searching keywords on stock return.

As mentioned above about the strong relationship between banks and fintech, and the impact of searching keywords on stock return, we argue that the fintech-related keywords might influence the bank return. To the best of our knowledge, no study has been conducted to investigate the impact of fintech-related search phrases on banks; consequently, we feel that doing the study is vital to add a fresh understanding into the link between fintech and banks in the digital era.

The case study of Vietcombank and Sacombank in Vietnam is chosen for the study because of two reasons. Firstly, in developing countries as Vietnam, the need for banking transactions with small value is vast, while the physical bank transaction offices are limited; thus, developing mobile banking applications is a mandatory requirement for banks to meet customer needs (Demirgüç-Kunt et al., 2018; Tripathy & Jain, 2020; Pousttchi & Dehnert, 2018). Through the use of mobile banking applications, customers can make transactions quickly. According to Google Play, the mobile banking application of Vietcombank and Sacombank has had many downloads. Secondly, in Vietnam, the state-owned bank is the critical factor of bank operation (Malik et al., 2016; Le et al., 2019). We contend that there is a distinction between state-owned banks and non-state-owned banks in terms of fintech adoption. As a result, Vietcombank and Sacombank have been picked to carry out the research. Vietcombank is regarded as a state-owned bank since the government is the largest stakeholder, owns the majority of the shares, and oversees the bank's operations, whereas Sacombank is strictly a joint-stock bank.

As a result, this study aims to perform a case study of Vietcombank and Sacombank in Vietnam to evaluate the impact of fintech-related keywords on bank return.

2. Literature Review

To the best of our knowledge, it is the first research to investigate the impact of fintech-related keywords on bank return; consequently, the background for this study is formed by studying related and existing articles on the impact of keywords on stock return and the impact of fintech on banks.

2.1 The impact of keywords on stock return

Bijl et al. (2016) used Google Trends to gather the number of search phrases to anticipate company returns in the S&P 500 in the United States from January 1, 2008 to December 31, 2013. The estimation findings revealed that Googling keywords had a negative influence on stock return. The authors concluded that the volume of searching keywords might predict stock return, and this relationship might change over time. From 2009 to 2016, Nguyen et al. (2019) applied the system-GMM to process the Fama-French model. According to the data, Googling keywords drastically reduced stock returns in the Philippines, Thailand, and Vietnam, and investors are sensitive to news on the internet. Using data from NIFTY 50 companies in the Indian stock exchange market from July 2012 to July 2017, Swamy and Dharani (2019) discovered a positive relationship between high searching keyword volume and stock returns, and domestic investors are more sensitive to searching keywords than foreign investors. On the Oslo Stock Exchange, Norway, from January 2, 2012 to January 2, 2017, Kim et al. (2019) did not find evidence of the significant relationship between searching keywords and abnormal stock return. However, the authors concluded that the volume of searching keywords might be related to the trading volume.

2.2 The impact of fintech on bank performance

The term "fintech" might be understood by various widening meanings. Firstly, the common meaning is to indicate the fintech companies, not intermediate financial institutions (Van Loo, 2018; Lee & Shin, 2018). Secondly, fintech is used to indicate the application of disruptive technologies for enhancing the performance of both intermediate financial institutions and non-intermediate financial institutions (Van Loo, 2018; Lee & Shin, 2018; Milian et al., 2019; Thakor, 2020). However, we received the term "fintech" for this research from Google Trends; hence, we feel that both definitions above cover the number of searches for "fintech." Additionally, as is the case in the majority of countries, mobile payment and peer-to-peer lending (P2P) are the main sectors or essential business models of the fintech industry in Vietnam, accounting for around 80-90 per cent of the overall market share (MBSecurities, 2018; Son et al., 2019). Therefore, we consider that the volume of searching terms "fintech," "mobile payment," and "peer-to-peer lendings" strongly relates to the development of fintech.

Depending on the strategy of fintech, the available publications reveal diverse outcomes of the influence of fintech on bank performance. Since the global financial crisis 2008-2009, the effect of fintech on the incumbents in the banking sector has been termed "two sides of the coin." The qualitative research by Lee and Shin (2018), Goldstein et al. (2019), and Milian et al. (2019) showed that the emergence of fintech would cut the operating cost, boost performance, and raise the efficiency of the bank. However, it is also a danger to the growth of the banks.

Regarding the quantitative research, the estimated findings concerning the interaction between fintech and banks are likewise diverse. Based on crawler technology and word frequency analysis, the fintech index of 60 banks in China from 2008 to 2017 was produced; Cheng and Qu (2020) found that there is a negative association between bank fintech index and bank credit risk. The increased deployment of disruptive technologies minimizes credit risk, raises bank profitability, and boosts bank performance. Wang et al. (2021) employed media's attention and factor analysis to assess fintech development in China. The authors studied that in the period 2011-2018, the link between fintech and bank risk-taking is U-shaped; firstly, the development of fintech lowered bank risk-taking, and subsequently, the excess of fintech growth raises bank risk-taking. In an investigation of the influence of fintech on the performance of 41 banks from 1998 to 2017 in Indonesia, Phan et al. (2020) assessed the fintech variable as the increase in the number of fintech enterprises. The data indicated that there is a detrimental influence of fintech expansion on bank performance.

Consequently, the impact of fintech on the bank is not clear; it might be positive or negative. This relationship concern is the motive for conducting the study to answer the question, "In developing countries such as Vietnam, how does fintech influence the bank?".

3. Data and Measurement

To address the study topic, we are gathering time series data on fintech-related terms and the return of Vietcombank and Sacombank in Vietnam from Google Trends and Vietstock between 2016w1 and 2021w2 (January 2, 2016 - March 13, 2021). This period was selected since, as of January 2016, Google Trends' mechanism for capturing Google Search Volume was modified in comparison to the previous period. Additionally, according to MBSecurities (2018), fintech has gained traction in Vietnam since 2016.

3.1 Fintech-related keywords

As mentioned above, the fintech-related keywords consist of "fintech," "financial technology," "mobile payment," and "peer-to-peer lendings." These keywords are also consistent with the findings in the fintech research field by Milian et al. (2019) and Alt et al. (2018). Besides that, these keywords are translated into Vietnamese for extracting from Google Trends. The Vietnamese form of these keywords is "Công nghệ tài chính" (translated from "fintech" and "financial technology"), "Thanh toán di động" (translated from "mobile payment"), and "Cho vay ngang hàng" (translated from "peer-to-peer lendings").

The volume of Google searches is determined by the frequency with which users collect terms. Google Trends is a tool for tracking Google Search Volume, a measure of "keyword" frequency on a scale of 0 to 100, referred to as the Google Searching Value Index (GSVI). Since the GSVI value is time-dependent, Kim et al. (2019), Huynh (2019), and Bijl et al. (2016) advocated using the Average Google Search Value Index (AGSVI) to perform the research. Based on Kim et al. (2019), Huynh (2019), and Bijl et al. (2016), in this study, the modified equation for AGSVI at week t with a standard deviation of GSVI for the past 52 weeks $\sigma_{GSVI,t,}$ as below:

$$AGSVI_t = \frac{GSVI_t - \frac{1}{52}\sum_{i=1}^{52} GSVI_{t-i}}{\sigma_{GSVI,t}} \quad (1)$$

In this study, the combination of $AGSVI_t^B$ (denote: B are the specific keywords), Fintech trend refers to the data taken from Google Trends. There are seven specific keywords, namely “fintech” (Fin), “financial technology” (FinT), and “Công nghệ tài chính” (FinTV), “mobile payment” (MoPa), “Thanh toán di động” (MoPaTV), “peer-to-peer lendings” (P2P), and “Cho vay ngang hàng” (P2PTV).

3.2 Bank returns

We collect the closing price of Vietcombank (code: VCB) and Sacombank (code: STB) at the last trading date of the week. If the last trading date is a day-off because of holidays, the previous date is chosen as an alternative. The data of stocks are the same and publicly on all statistical security organizations. In this study, we choose Vietstock for collecting data.

Based on Kiymaz and Berument (2003), the individual bank return is calculated as below:

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

Where, r_t is the return of bank at the end of week t; P_t and P_{t-1} are the closing prices of the bank stock at the end of week t and t-1, respectively.

According to equation (2), the return of Vietcombank (RVCB) and return of Sacombank (RSTB) are computed.

4. Data Analysis Process and Results

To clarify the influence of fintech-related keywords on the return of Vietcombank and Sacombank, the data analysis process and results are followed as below:

4.1 Descriptive statistics

For getting insight into the feature of data, the descriptive statistical variables are shown in Table 1.

As shown in Table 1, the mean of RVCB is more than that of RSTB over time, while the standard deviation of RVCB is less than that of RSTB; this suggests that during the period, the bank stock of VCB generated a better rate of return with fewer fluctuations than STB. The means of Fin, FinT, and FinTV indicate that users prefer the term "fintech" over "financial technology" and "công nghệ tài chính" when searching on Google; and because the mean of FinTV is negative, we argue that the term "công nghệ tài chính" is irrelevant and should be replaced by the English terms "fintech" and "financial technology." Similarly, the English word "mobile payment" is preferable to "Thanh toán di động." The search terms "peer-to-peer lendings" and "cho vay ngang hàng" had the same number of results. However, the word "fintech" is a very popular search term.

Table 1 : Descriptive statistics

Variable	Explanation	Obs.	Mean	S.D.	Min	Max
RVCB	The return of Vietcombank and Sacombank, respectively	272	.00130	.01919	-.13245	.05690
RSTB		272	.00079	.02118	-.07688	.06012
Fin	AGSVI of the keyword “fintech,” “financial technology,” “công nghệ tài chính,” “mobile payment,” “Thanh toán di động,” “peer-to-peer lendings,” and “cho vay ngang hàng,” respectively	272	.27721	1.23663	-2.07608	9.5706
FinT		272	.04155	1.13813	-.73544	7.07243
FinTV (*)		272	-.02426	1.01564	-1.18054	6.36984
MoPa		272	.08758	1.10203	-1.39235	4.58743
MoPaTV (*)		272	.06897	1.11998	-.83873	5.47273
P2P		272	.03447	1.05166	-2.27420	4.72845
P2PTV (*)		272	.03822	1.04524	-.58953	7.07243

Source: The Authors

4.2 Unit root test

The mandatory requirement of a time-series variable is that the variables must be stationary. This study uses the Dickey-Fuller and Phillip-Perron methods for the unit root test (or stationary tests). The null hypothesis is that the variable (or the series) has a unit root. If the variable is not stationary at the level, the first difference of variables will be an alternative for testing.

Table 2 shows a consistency between the estimation results of the Dickey-Fuller test and the Phillips-Perron test. All null hypotheses are rejected at the 1% confidence level, which means all variables are stationary at the first level. The original variables are eligible for use in the following

4.3 Optimal lag selection

Next, based on Lütkepohl (2005), Pfaff (2008), and Ivanov and Killian (2001), the test of lag-order selection is conducted. The estimation statistics consist of the Akaike's Information Criterion (AIC), the Hannan and Quinn Information Criterion (HQ), the Schwarz's Bayesian Information Criterion (SC), and the Prediction Error (FPE), which are used for selecting the optimal lag. The estimation results are given in Table 3.

Table 2: Unit root test

Variable	Dickey-Fuller test		Phillips-Perron test	
	t-statistics	Null hypothesis	t-statistics	Null hypothesis
RVCB	-14.708***	Reject	-14.651***	Reject
RSTB	-16.126***	Reject	-16.128***	Reject
Fin	-15.625***	Reject	-15.831***	Reject
FinT	-17.856***	Reject	-17.823***	Reject
FinTV	-9.439***	Reject	-9.396***	Reject
MoPa	-15.809***	Reject	-15.929***	Reject
MoPaTV	-15.247***	Reject	-15.363***	Reject
P2P	-15.469***	Reject	-15.512***	Reject
P2PTV	-14.716***	Reject	-14.662***	Reject

*Note: *** means significant at 1% level*
Source: The Authors

Table 3: The lag-order selection

Lag	RVCB				RSTB			
	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	.001033	15.8279	15.871*	15.9351*	.001186	15.9659	16.0089*	16.0731*
1	.000986*	15.7806*	16.1681	16.7453	.001149*	15.9342*	16.3217	16.899
2	.001184	15.9624	16.6943	17.7847	.00138	16.1157	16.8476	17.938
3	.001508	16.2019	17.2783	18.8818	.001742	16.3461	17.4224	19.0259
4	.001915	16.4349	17.8557	19.9723	.0022	16.5736	17.9944	20.111

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

Table 4: The estimation results of the cointegration test

Lag	RVCB				RSTB			
	LL	Eigenvalue	Trace Statistic	5% critical value	LL	Eigenvalue	Trace Statistic	5% critical value
0	-2731.7919		1326.4645	156.00	-2762.4439		1339.8161	156.00
1	-2611.69	0.58782	1086.2767	124.24	-2643.5508	0.58415	1102.0299	124.24
2	-2502.0882	0.55467	867.0570	94.15	-2538.0126	0.54108	890.9535	94.15
3	-2410.3668	0.49182	683.6142	68.52	-2439.6837	0.51600	694.2958	68.52
4	-2325.591	0.46509	514.0627	47.21	-2353.299	0.47140	521.5264	47.21
5	-2248.5401	0.43371	359.9608	29.68	-2271.8148	0.45193	358.5579	29.68

Source: The Authors

According to Ivanov and Killian (2001) and Huynh (2019), the AIC statistic is a priority for choosing optimal lag for this data. Therefore, the optimal lag of one (1) is fitted for the data.

4.4 Cointegration test

Following Lütkepohl (2005) and Johansen (1988), we estimate the cointegrating rank statistics using the vector error-correction model (VECM) with a latency of one.

Table 4 indicates that there is no cointegrating relationship between fintech-related keywords and bank return. The pair of variables do not persist in the long term. Therefore, the VAR estimation is used to investigate the influence of fintech-related keywords on the return of Vietcombank and Sacombank.

4.5 Granger causality analysis

Next, the VAR Granger causality analysis is conducted to return Vietcombank and Sacombank to clarify the fintech-related keywords that cause a return change. The estimation results are presented in Table 5. It shows no fintech-related keywords, which have strong evidence to cause the return of Vietcombank and Sacombank in the sample period. However, we explore that the participants seem not to search only one keyword. There is strong evidence of looking for fintech and the segments of fintech. For example, the pairs of keywords "peer-to-peer lendings" and "financial technology"; "Cho vay ngang hàng" and "financial technology"; and "Thanh toán di động" and "Fintech."

4.6 OLS estimation

Furthermore, we also employ the OLS model for estimating the impact of fintech-related keywords on the return of Vietcombank and Sacombank. The estimation results are presented in Table 6. It gives that model 1 is not significant, which means the keywords and the lag one week of Vietcombank return could not explain the Vietcombank return change. However, model 2 is significant at level 10%, which means the independent variables in the model might explain the change of Sacombank return, namely, the coefficients of the lag one week of Sacombank return has positive significance with the Sacombank return at level 5%; the keyword "financial technology" is negatively significant at level 1%; the keyword "Thanh toán di động" is negatively significant at level 10%, and the keyword "Cho vay ngang hàng" is positively significant at level 10%.

Table 5: Granger causality for variables

Variable	RVCB	Fin	FinT	FinTV	MoPaTV	MoPa	P2P	P2PTV	All
RVCB	-	1.274	1.1136	.27125	.01547	.01823	.96251	.70715	3.8759
Fin	2.5232	-	1.8634	.06009	.01157	.82022	1.6433	.07727	7.8964
FinT	1.164	.03614	-	.60606	1.1567	.7338	2.1804	.1572	5.9452
FinTV	.56454	1.7199	.04098	-	.70821	.56503	.344	.067	4.0302
MoPaTV	.89736	3.6458*	.94326	.02485	-	.8745	1.8048	.3779	8.3021
MoPa	.59163	.77957	.12493	.20136	.17328	-	1.2004	2.572	6.2251
P2P	.55919	.02805	2.9381*	.01141	.02453	.51353	-	.0053	5.026
P2P TV	1.6289	.36953	3.5786*	1.9031	.10378	.01338	.19272	-	8.9333
Variable	RSTB	Fin	FinT	FinTV	MoPaTV	MoPa	P2P	P2PTV	All
RSTB	-	1.6947	.55113	.20191	2.8959	.08082	.09453	.04834	4.7805
Fin	2.6774	-	3.5425*	.12044	.01397	.61044	1.2142	8.3e-05	8.0537
FinT	.06527	.00448	-	.52761	1.0852	.83326	2.4689	.22987	4.8271
FinTV	.02009	1.5162	.11022	-	.66857	.50755	.27367	.09767	3.4788
MoPaTV	.18151	3.3727*	.8277	.03567	-	.8185	1.9724	.36507	7.5667
MoPa	2.1968	.76997	.27083	.20114	.12017	-	1.2313	2.1053	7.8636
P2P	1.2351	.02011	2.5614	.01338	.04677	.51715	-	.03026	5.7131
P2P TV	.75282	.61121	4.9021**	2.104	.09022	.00087	.09487	-	8.0337

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

Table 6: OLS estimation results

Variable	Model 1 (RVCB)		Model 2 (RSTB)	
	Coef.	t-statistic	Coef.	t-statistic
RVCB (t-1)	.072383	1.14	-	-
RSTB (t-1)	-	-	.151305**	2.22
Fin	.0012882	1.20	-.000471	-0.41
Fin (t-1)	.0010236	1.00	.0010363	0.94
FinT	-.0022825**	-2.02	-.0031768***	-2.61
FinT (t-1)	-.0010646	-0.94	-.000502	-0.41
FinTV	.0013635	1.01	.0009993	0.69
FinTV (t-1)	-.0012473	-0.93	-.0011835	-0.82
MoPaTV	-.0006658	-0.62	.0008497	0.74
MoPaTV (t-1)	-.0001917	-0.18	-.0020914*	-1.84
MoPa	-.0007846	-0.72	-.0004639	-0.39
MoPa (t-1)	-.0001118	-0.10	.00071	0.61
P2P	.0012717	1.10	.0007372	0.59
P2P (t-1)	.0007737	0.67	-.0001826	-0.15
P2PTV	.0008757	0.75	.0022208*	1.77
P2PTV (t-1)	-.0011695	-1.01	-.000183	-0.15
Cons	.0007557	0.61	.0003556	0.27
N	271		271	
R-squared	0.0533		0.0853	
Statistics	0.96		1.59*	

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

5. Discussion

Based on the estimation results above, we explore some interesting findings.

There is a preference for using fintech-related keywords in English form to replace the same in Vietnamese form. We discuss that it is suitable with the current context of Vietnam, caused by (1) Vietnam being deeply integrated into the international community, and English being more prevalent in daily life, with a preference for use by children and adolescents (Tran & Tanemura, 2020; Bui & Nguyen, 2016); and (2) the term "fintech" is relatively new, with a strong connection to the digital revolution and youth (Tran & Tanemura, 2020; Bui & Nguyen, 2016; Milian et al., 2019; Thakor, 2020). The literature review shows Granger causality between fintech-related keywords, namely the causality of "fintech" and the two largest segments of the fintech business model. We discuss that it can reflect the fintech literacy of the users, who seem to understand the fintech sector and the business models of the fintech. Morgan and Trinh (2020) found evidence of a positive relationship between financial literacy and an individual's awareness and use of fintech products in Vietnam. Moreover, under the rapid development of internet infrastructure in Vietnam, the basics of fintech products (payment/transfer and credit) might easily meet customer needs; thus, it might be critical to enhance customer awareness about fintech.

By the VAR Granger causality approach, there is no evidence of the influence of fintech-related keywords on the return of Vietcombank and Sacombank. However, by the OLS approach, we explore the difference in the impact of fintech-related keywords on the return of state-owned banks and private banks; namely, fintech-related keywords do not influence the return of Vietcombank, but they influence Sacombank return. These reasons might explain it. Firstly, Google Searching Value Index reflects the volume of searching keywords by both investors and normal users; thus, the probability might be in the sample's time scale. The typical users are more inquisitive and interested in fintech than the investors. Secondly, Vietcombank and Sacombank invest in applying disruptive technology, but it is not the critical factor influencing bank performance. In developing countries as Vietnam, the bank can increase profit by expanding the scale or supporting monetary policy (Nguyen et al., 2017). Thirdly, Sacombank is a private bank whose size is smaller than Vietcombank; thus, the former is more agile in adaptation with the context of fintech than the latter. However, Pham et al. (2021) report that information technology investment reduces bank efficiency in Vietnam. We believe this may account for the disparity in the effect of fintech-related terms on the return of Vietcombank and Sacombank.

6. Conclusion

Investigation of the impact of fintech on banks has attracted a vast number of scholars. This study provides a new aspect about the impact of internet users' fintech attention on banks. Based on Google Trends, the volume of fintech-related keywords was extracted for the study. In the case study of Vietcombank and Sacombank in Vietnam, the research concern "Do fintech-related keywords on searching Google influence bank return?" is conducted to answer the question. Firstly, by the VAR Granger causality approach, the fintech-related keywords do not influence the return of Vietcombank and Sacombank. Secondly, the OLS approach has no evidence of the impact of fintech-related keywords on Vietcombank return. However, the impact of "Cho vay ngang hàng" is significantly positive, and of "financial technology" and lag one week of "Thanh toán di đÙng" are significant negative with the return of Sacombank. Additionally, we explore the preference of using fintech-related words in English form for searching on Google and the positive performance about fintech awareness of the internet users.

The study has some limitations. Firstly, the volume of searching keywords might be biased by the number of normal internet users (non-investors). Therefore, to reduce data bias, we propose that the next study limit the bank's information resources. For example, searching the frequency of fintech-related keywords on the bank's annual reports and other related documents. Secondly, Vietcombank and Sacombank might not reflect the whole performance of Vietnamese banks on the stock market. The next study could focus on formulating the banking system's return index instead of investigating individual banks or focusing on investigating the specific kind of bank (eg., private bank, or state-owned bank).

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