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Relationship between fintech by Google search and bank stock return: a case study of Vietnam

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Abstract

Due to the ongoing global debate regarding the relationship between fintech and banks, including developing countries, this study aims to investigate this relationship in the case of Vietnam, an emerging nation. The study analyzes the relationship between fintech search and bank stock returns, which are measures of fintech and banks, respectively. The time series data for fintech and bank stock returns were obtained from Google Trends and Vietstock, respectively. Exploratory factor analysis was utilized to derive the fintech variables, while the bank stock return variable was calculated using a basket of eight listed banks from 2017w46 to 2021w46. The results were estimated using the vector autoregression and Granger causality method and validated with the copula method. A key finding of this study is the presence of a simultaneous negative change and bidirectional causality between bank stock returns and fintech lending. Furthermore, several other interesting findings were discovered: (1) the causal relationship from fintech to bank stock returns is weaker compared with the opposite direction; (2) unidirectional causality exists between different types of fintech, such as influence from FinFintech to FinLending, from FinPayment to FinLending and FinWallet, from FinMoney to FinFintech, from FinWallet to FinLending, and from FinProduct to FinFintech; and (3) there is an equal occurrence of simultaneous increase or decrease between bank stock returns and certain types of fintech, specifically between BankReturn and FinPayment, BankReturn and FinLending, as well as BankReturn and FinWallet. These findings shed light on the complex relationship between fintech and banks, offering insights that contribute to our understanding of this dynamic interplay in the context of Vietnam's emerging fintech landscape.

Keywords: Fintech, Bank stock return, Vietnam, Google, VAR-Granger, Copula

JEL Classification: G30, O32, Q55

Introduction

Fintech is a compound word comprising "financial" and "technology," representing the utilization of disruptive technologies to improve the performance of the finance market (Puschmann 2017). Since the 2008–2009 Global Financial Crisis, the fintech sector has been recognized as an integral part of the finance market (Arner et al. 2015, 2020; Lee and Shin 2018). The development of fintech has sparked a scholarly debate concerning its relationship with traditional commercial banks (Milian et al. 2019). In quantitative studies, the findings on this relationship are not consistent. Phan et al. (2020) suggested that fintech reduces bank profitability. Conversely, Li et al. (2017) demonstrated that fintech support enhances bank performance. However, Wang et al. (2021) identified a U-shaped pattern in the relationship between fintech and bank risk-taking, where bank risk-taking initially increases but subsequently decreases with the advancement of fintech. Given these contrasting outcomes, further investigations are necessary to establish a comprehensive understanding of the relationship between fintech and banks, presenting a significant research problem.

The existing quantitative publications about fintech and bank performance have revealed various ways to measure the fintech variable. Ky et al. (2019) measured the fintech variables of 170 banks from 2009 to 2015 based on the involvement of banks with mobile money via mobile network operators. In detail, the fintech variables consist of dummy variables (involving or not), the number of involving years, the number of users, and transaction values. The finding revealed a strong positive relationship between fintech and bank performance. In the United Arab Emirates, Saudi Arabia, and Bahrain, Almulla and Aljughaiman (2021) formulated the bank fintech score from the existence of fintech services in a bank and used the number of fintech firms to measure fintech variables from 2014 to 2019. The estimation results revealed that bank fintech is a negative factor in bank profitability, and the growth of fintech firms negatively affects conventional banks but is insignificant for Islamic banks. Cornelli et al. (2020) and Nguyen et al. (2021) used the ratio of fintech credit to GDP to proxy fintech variables and investigated its impact on bank performance. Based on the dataset of 73 countries from 2013 to 2018, Nguyen et al. (2021) indicated that fintech credit is a negative factor in bank profitability, but with the moderating role of regulation, fintech credit is positive for bank stability. Based on the database of the World Bank, Sadigov et al. (2020) used the indices of using mobile phones to access an account with a financial institution and using the internet to pay bills to proxy fintech development. The finding revealed that fintech development is a positive factor in economic growth. Further, Cheng and Qu (2020) used crawler technology and a word frequency technique to measure the fintech variable. Sheng (2021) used the fintech index to indicate the fintech development of 31 provinces in China from 2011 to 2018, which the Institute of Digital Finance provided. Phan et al. (2020) measured the fintech variable as the number of fintech startup companies, whereas Asmarani and Wijaya (2020) measured fintech variables as fintech funding frequency and fintech funding value. Based on the studies mentioned above and our knowledge, it appears that the use of Google search to measure the fintech variable is rare, representing a research gap in the relationship between fintech and bank performance. Therefore, conducting a study using Google search as a measurement tool would fill this gap and contribute to a better understanding of fintech measurement and its relationship with bank performance in the digital era.

There is a significant link between internet search data and socioeconomic issues (Mellon 2013, 2014). Mellon (2014) proved that Google search is a valuable tool for measuring fuel prices, the economy, immigration, and terrorism. De Area Leão Pereira et al. (2018), Huynh (2019), Mellon (2014), Nghiem et al. (2016), and Nuti et al. (2014) applied Google search to measure users' perception of the Trump's effect, entrepreneurs, salience, conservation, and health care, respectively. Fintech development is based on the internet platform and disruptive technologies, such as big data, machine learning, and blockchain (Gomber et al. 2017; Milian et al. 2019). The amount of fintech information and the volume of searching fintech-related keywords in cyberspace reflect fintech development over time. Zhi Da and Gao (2011) stated that the volume of searching keywords on Google indicates investor attention, which might affect the stock index. De Area Leão Pereira et al. (2018) used Google search to measure the Trump effect and investigated its impact on the stock index. The finding revealed that the Trump effect is positive with the North American stock index and negative with the Mexican stock index. Salisu and Vo (2020) indicated that health news regarding coronavirus (COVID—19) measured by Google search negatively affected stock returns. Choi et al. (2020) revealed that the relationship between attention to climate change by Google search and stock return is moderated by firms' degree of carbon emissions. Based on these studies and empirical evidence about the relationship between fintech and bank performance, it is possible to use Google search to measure fintech variables. Moreover, fintech measured by Google search might have a significant relationship with bank stock return on the financial market. Investigating this relationship is the primary goal of this study.

Building on the aforementioned argument, our concern lies in determining whether there is a relationship between searching for fintech on Google and bank stock returns. The search volume for fintech serves as a proxy for measuring the development of the fintech industry, capturing internet users' attention toward fintech in cyberspace. According to Pham et al. (2021), the Google search volume index of fintech-related keywords covers two types of fintech—fintech companies and bank fintech (bank utilizes disruptive technologies). Hence, in this study, the development of the fintech industry includes internet users' attention to fintech companies and bank fintech. Pham et al. (2021) used the Average Google Search Value Index (AGSVI) to measure the fintech variable. However, this measure does not indicate the group effect of similar fintech-related keywords on bank stock return. We aim to integrate the fintech variable measurement techniques in the studies by Cheng and Qu (2020) and Pham et al. (2021). Based on the AGSVI, the exploration factor analysis and the maximum–minimum processing are employed to reduce the estimated variable and increase the reliability of the data analysis process, respectively. To the best of our knowledge, this is a novel measurement, and investigation of its relationship with bank stock return is the first study in this field.

In this study, Vietnam has been selected as the context for investigating the relationship between Google search activity for fintech and bank stock returns. There are several reasons behind this decision. First, Vietnam is a developing country in which the fintech industry has experienced significant growth. According to Statista, the number of fintech users in Vietnam doubled from 26.59 million in 2017 to 53.80 million in 2021. Transaction values also increased by approximately 2.5 times during this period, from 7.3 billion US dollars in 2017 to 18.1 billion US dollars in 2021. Projections indicate that by 2025, there will be 75.39 million users and 35.2 billion US dollars in transactions. Furthermore, the number of new fintech firms grew by 170% from 2017 to 2021, and in 2021, 26.2% of internet users in Vietnam utilized mobile payment monthly. Second, the Vietnamese Government has implemented regulations that establish a robust legal framework for fintech development. Notable examples include Decision No. 2655/2019/QĐ-NHNN, which focuses on the development of information technology strategy in the banking industry; Decree No. 80/2016/NĐ-CP, which pertains to electronic payment and e-wallets; and Decision No. 999/2019/QĐ-TTg, which establishes the fintech regulation sandbox. These regulatory measures have facilitated the growth of fintech in Vietnam. Third, in developing countries like Vietnam, fintech plays a crucial role in promoting financial inclusion, a goal that traditional financial institutions may not fully address. Fintech services offer essential banking products, such as payment and lending, to customers who have limited access to traditional financial services, particularly low-income individuals in rural areas (Demirguc-Kunt et al. 2018; Morgan and Trinh 2020). Based on these factors, we hypothesize that the development of fintech in Vietnam may have a substantial impact on bank performance. Therefore, conducting a study to explore the relationship between fintech and bank performance and using stock returns as a proxy in the Vietnamese context would be highly valuable.

This study makes two significant contributions to the literature. First, it introduces the use of Google search as a novel measure for fintech variables. Second, it presents empirical evidence on the relationship between fintech information search and bank stock returns in Vietnam, which holds substantial relevance for stakeholders in the fintech and banking industry in Vietnam.

The next sections are organized as follows. Section "Theoretical backgrounds" is the theoretical background, where the relevant publications are reviewed to state the research topic on the fintech concept, Google search in research, and fintech and bank stock index. Section "Research methodology" is the research methodology, comprising the research model, measurement variables, data collection, and data analysis. The estimation results and discussions are included in section "Results and discussion", whereas section "Conclusions" is the conclusion, highlighting the main features of the study, recommendations, limitations, and future research directions.

Theoretical backgrounds

In this section, our strategy is to select high-quality articles from the Web of Science and/or Scopus databases for review. The selection procedure is as follows. First, the Google Scholar platform is used to search relevant keywords in the research topic, such as fintech, Google search, stock, and bank, and combine these terms in various ways. Further, the search outcomes are managed by the time scale—the last 15 years. Second, if the journal's name of the article is in the Web of Science or/and Scopus database, the article will be selected. Based on this approach, three main strands that form the theoretical background are proposed in the following subsections: (i) fintech concept, (ii) Google search in research, and (iii) fintech and stock return.

Fintech concept

There are many fintech concepts. As mentioned above, Puschmann (2017) stated that fintech is a compound word of the words "financial" and "technology," which means using disruptive technologies to improve the performance of the finance sector. According to Vives (2017), "Fintech may be understood as the use of innovative information and automation technology in financial services." Giving more detail, Milian et al. (2019) considered fintech as the technology used to provide financial products by suppliers in the finance market. This concept is consistent with the views of most scholars, such as Alt et al. (2018), Breidbach et al. (2019), and Thakor (2020). Based on these views and our knowledge about fintech, we propose that fintech can be understood from two perspectives. First, bank fintech refers to technological applications to enhance the performance of traditional financial institutions in the finance market, including types of banks. Second, fintech-outside refers to financial products provided by non-intermediate firms (generally called fintech companies) who are advanced in using disruptive technologies to supply suitable financial products to customers.

Google search in research

There is a significant link between internet search data and socioeconomic issues (Mellon 2013, 2014). One of the most powerful internet search engines is Google, which provides more advanced data in terms of cost and availability than conducting a survey. Moreover, Google search data are continuously updated (hourly, daily, weekly, monthly, and yearly) and are sorted by time and region. When querying specific keywords on Google Trends, the time series of the volume of searching keywords is shown, called the Google searching volume index (GSVI). The scale of GSVI is from 0 (zero) to 100, indicating the frequency of capturing keywords from lowest to highest.

Google search has become a significant data source and is acceptable in social science research. Mellon (2013) confirmed an essential link between the volume of searching keywords on Google and socioeconomic issues. In addition, Mellon (2014) proved that Google search is a valuable tool for measuring fuel prices, the economy, immigration, and terrorism in the US. Further, the power of Google search is validated in the conservation field (Burivalova et al. 2018; Nghiem et al. 2016; Troumbis and Iosifidis 2020), in the prediction of COVID− 19 (Ayyoubzadeh et al. 2020; Husnayain et al. 2020; Lin et al. 2020), and other fields, including finance.

Li et al. (2021), Zhang and Tang (2016), and Huang et al. (2020) agree that the search engine is an interesting measure to reflect investor attention in finance research. It measures public attention on cyberspace through search volume. Utilizing Google search to measure investor attention and estimate the volatility of financial assets has attracted the attention of many scholars. There was a negative relationship between Google search volume and stock returns in the US market from 2008 to 2013 (Bijl et al. 2016), and the same relationship existed in the Philippines, Thailand, and Vietnam markets from 2009 to 2016 (Nguyen et al. 2019). In contrast, from 2012 to 2017, Ekinci and Bulut (2021) and Swamy and Dharani (2019) found a positive impact of Google search on the stock returns in the Borsa Istanbul and the Indian market, respectively. However, in Norway, Kim et al. (2019) s tated that this relationship is insignificant for a sample of 28 firms from 2012 to 2017. Besides the stock returns side, other financial assets have also been investigated in connection with Google searches, such as foreign currency (Smith 2012), cryptocurrency (Kristoufek 2013; Lin 2021), fossil energy (Qadan & Nama 2018), and commodity market (Bahloul & Bouri 2016).

Fintech and stock return

In many quantitative studies, the relationship between fintech and stock returns has been examined through various methodologies. These findings contribute significantly to our understanding of the relationship between fintech and stock returns.

Dranev et al. (2019) utilized the event window approach to investigate the impact of fintech mergers and acquisitions (M&A) on abnormal stock returns of companies in the US, Canada, Europe, China, and India. They discovered that fintech M&A has a positive effect on the short-term abnormal stock returns of acquired firms but is not significant in the long term. Additionally, they found that returns in developed countries are higher than those in developing countries. Employing the same method as that of Dranev et al. (2019) to analyze Chinese bank stock prices, Zhang and Zhuang (2020) found that fintech events positively affect bank stock returns in the short term.

In the US, Li et al. (2020) investigated the relationship between fintech stock returns and financial institutions' stock returns using the risk spillover approach of Granger causality. Their findings indicated that risk spillovers between the two variables occur in various tails (left, right, and central tails). However, during the downside period (left tail), the spillovers are stronger, and there is a positive effect of the fintech variable on the stock of financial institutions. Furthermore, Chen et al. (2021) used the spillovers approach of Diebold and Yılmaz (2014) to examine the spillovers between fintech and financial institutions. Their results revealed a more substantial effect from return and volatility in banks to fintech compared with the opposite direction.

Li et al. (2017) employed the capital asset pricing model with three and five factors to estimate the impact of fintech on incumbent retail bank stock returns in the US from 2010 to 2016. They found that the fintech variable has a positive effect on bank stock returns, although the effect is relatively weak. The authors also discussed that fintech was not a threat to incumbent banks during the sample period but suggested that the position of fintech would change rapidly in the future. Applying the methodology of Li et al. (2017) to the Indonesian market, an emerging country, Asmarani and Wijaya (2020) found that fintech does not influence retail bank stock returns.

Moreover, numerous quantitative studies have confirmed the significant relationship between fintech and banks, particularly in terms of bank performance, which may also impact bank stock performance. We contend that this relationship serves as a crucial reference point. Phan et al. (2020) and Zhao et al. (2022) suggested that the rise of fintech leads to a decrease in bank profitability. Additionally, Sheng (2021) found that fintech development increases credit supply to SMEs. Wang et al. (2021) observed a U-shaped pattern in the relationship between fintech and bank risk-taking. Furthermore, Chen et al. (2021) demonstrated that fintech enhances customer satisfaction and improves employee work efficiency. These and other noteworthy studies have provided valuable insights into the relationship between fintech and bank stock.

The literature review reveals that there is a significant relationship between bank stock returns and fintech. However, the different estimation methods employed in these studies led to inconsistent findings regarding the nature of this relationship. In this study, the objective is to introduce a novel approach for measuring fintech variables using Google search data and apply the vector autoregression and Granger causality (VAR-Granger) and copula methods to estimate this relationship.

Research methodology

Based on the theoretical background section above, the research methodology is designed as follows:

Data

According to MBBank (2021), MBSecurities (2018), and Morgan and Trinh (2020), since 2016, the fintech sector has dramatically risen, which is a milestone in fintech development in Vietnam. Therefore, in this study, 2016 is considered the starting point for data collection to investigate the relationship between fintech and bank stock return in a case study of Vietnam.

The data for this study are collected from two sources. First, Vietstock, a reputable statistical organization in the Vietnamese stock exchange market, provided the necessary information, including the opening price, closing price, trading volume, and the number of shares outstanding, which are used to compute the bank stock index and bank stock return variables. Second, the search index volume for each keyword was retrieved from Google Trends.

According to Swamy and Dharani (2019) and Bijl et al. (2016), weekly data appropriately reflect investor attention to changes in stock movement on the market. Therefore, the weekly data from 2016w46 to 2021w46 is used for this study. However, due to the downloaded data period from Google Trends, the computed fintech variables are valued at less than 52 weeks compared with the raw data. Therefore, the sample for analysis is from 2017w46 to 2021w47.

Measurement

Fintech variables

Before utilizing Google Trends to extract fintech variables, a formulation of fintech-related keywords is necessary. The term "fintech" is a widely recognized compound word that combines the words "finance" and "technology," making the keywords "fintech" and "finance technology" essential, as they belong to the general dimension of fintech. In addition to these compulsory keywords, it is important to expand the list of fintech-related keywords to gain insights into the relationship between fintech and banks. Reports from Statista (2021a, 2021b) and UOB (2020, 2022) highlight payment and peer-to-peer (P2P) lending as the two largest segments in the fintech industry in Vietnam. These segments significantly influence consumer behavior toward banking product usage. Lee and Shin (2018) emphasized how payment and lending have reshaped behaviors associated with traditional banking activities, such as saving, lending, borrowing, and transferring funds. Gomber et al. (2017) noted that fintech offers advanced products that have become integral to social life, especially in the realm of payment and lending platforms. Furthermore, Alt et al. (2018), Goldstein et al. (2019), Kou et al. (2021a, b), Puschmann (2017), and Suryono et al. (2020) have demonstrated a significant scholarly and customer interest in fintech business models and fintech products related to payment and lending. Therefore, in this study, along with the previously mentioned general dimension of fintech, it is crucial to include keywords related to payment and lending to comprehensively explore the subject.

Relying on the highlighted points in the studies by Goldstein et al. (2019), Lee and Shin (2018), Gomber et al. (2017), Anagnostopoulos (2018), Buchak et al. (2018), Milian et al. (2019), Alt et al. (2018), Wang et al. (2021), Cheng and Qu (2020), Sangsavate et al. (2019), and Cao et al. (2021), the term "peer-to-peer lending" is selected for the fintech lending dimension, and the terms "mobile money," "e-money," "mobile payment," "mobile wallet," and "e-wallet" are selected for the fintech payment dimension. Then, these selected keywords are translated into Vietnamese from English by three experts in the Vietnamese fintech industry (a commercial bank manager, a fintech company chief, and a lecturer in the finance banking department of Can Tho University). Finally, 16 fintech-related keywords are selected and presented in Table 1.

Then, the GSVI of the 16 keywords is collected from Google Trends. $GSVI^{\text{peer-to-peer lending}}$ is close to zero, which might be because "peer-to-peer lending" is not a favorite in Vietnam. The GSVIs of the remaining 15 keywords are valuable. However, as the value of GSVI depends on the period of the downloaded data (as we mentioned above), the raw GSVI is not significant for analysis. Thus, Bijl et al. (2016) and Kim et al. (2019) proposed the AGSVI as an alternative index. Following Bijl et al. (2016), Kim et al. (2019), and Huynh (2019), we apply the $AGSVI_t^k$ equation of the GSVI at week t of keyword k with $\sigma_{GSVI_t^k}$ of the standard deviation of GSVI for the past 52 weeks to measure the components of fintech variables.

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

Next, following Cheng and Qu (2020), we applied the exploratory factor analysis (EFA) method to reduce the number of fintech variables and confirm the significance of choosing keywords. The estimation result of the EFA method indicates that (1) KMO = 0.501 > 0.5, Bartlett's Test = 128.619, and Sig. = 0.059 < 10%, implying that the EFA is suitable for the data; (2) six eigenvalues are higher than one (the closest eigenvalue is 1.092), and Cumulative = 0.522, indicating that six significant factors might explain 52.26% of changes in 15 inputs ($AGSVI^k$). As this sample has 209 observations, the absolute value of the threshold of factor loading for determining the composition of the representative variables is 0.5 (Hair et al. 1998). The estimation indicates that the $AGSVI^{\text{mobile payment}}$ does not meet the requirement; thus, it is not used for computing the representative variable value. Based on 14 significant components, we determine that there are 6 fintech variables—*FinWallet, FinMoney, FinFintech, FinProduct, FinLending, and FinPayment*—and their respective components,

Table 1 Fintech-related keywords for extraction

Dimension	Keywords in English	Keywords in Vietnamese
Fintech in general	Fintech, financial technology	Công nghệ tài chính
Fintech lendings	Peer-to-peer lendings	Cho vay ngang hàng, cho vay online, cho vay đồng cấp
Fintech payment	Mobile money, e-money, mobile payment, mobile wallet, e-wallet	Tiền điện tử, thank toán di động, thanh toán online, ví điện tử

as presented in Table 2. The classification matches the meaning of keywords and the current situation of the fintech industry in Vietnam. The value of the representative variables is computed by the regression option on SPSS version 23. Further, following Cheng and Qu (2020), the value of the fintech variables will be standardized from 0 (zero) to 1 (one) using the maximum–minimum processing.

Bank stock return variable

According to the State Bank of Vietnam, as at the end of 2021, there were 31 commercial banks, including 19 listed banks in two official stock exchanges (HOSE and HNX), but 11 banks were listed after 2016. We selected 8 listed banks (trading code: VCB, BID, CTG, MBB, ACB, STB, SHB, and EIB) to compute the bank stock return variable (denote: *BankReturn*). These banks were selected because they matched the requirement of continuous trading in the sample period (match with data from Google search). Moreover, they are the biggest in terms of authorized capital and are well-known in the Vietnamese banking industry. The authorized capital of the 8 selected banks comprises 46.99% of the total authorized capital of 31 commercial banks (230,839 billion VND out of 491,242 billion VND). According to the dataset of 19 listed banks on Vietstock, the 8 selected banks accounted for 68.90% of the total assets and 57.59% of the total market capitalization at the end of 2021. Therefore, these banks meet the sample selection criteria. The raw data for calculating the bank stock return variable is provided by Vietstock—a trusted statistical organization in Vietnam. *BankReturn* is computed as follows:

Based on the studies by Kim et al. (2019), Kiymaz and Berument (2003), Truong et al. (2020), and Nguyen et al. (2019), BankReturn at time t is calculated by the equation below:

$$BankReturn_t = log(BankIndex_t) - log(BankIndex_{t-1}) = log\frac{BankIndex_t}{BankIndex_{t-1}} \quad (2)$$

Table 2 Factor loading value

Component	Represent variable or Fintech variable					
	FinWallet	**FinMoney**	**FinFintech**	**FinProduct**	**FinLending**	**FinPayment**
1 Mobile wallet	0.739					
2 E-wallet	0.582					
3 Mobile money		0.635				
4 Tiền điện tử*		− 0.618				
5 Công nghệ tài chính*			− 0.630			
6 Fintech			0.625			
7 Financial technology			0.590			
8 Thanh toán online*				0.654		
9 E-money				0.619		
10 Cho vay ngang hàng*				0.597		
11 Cho vay online*					0.703	
12 Cho vay đồng cấp*					0.680	
13 Ví điện tử*						0.695
14 Thanh toán di động*						0.549

*Denotes the Vietnamese language

Source: The Authors

$$BankIndex = \frac{CMV}{BMV} \times 100 \tag{3}$$

where CMV is the current market value, and BMV is the base market value.

$$CMV = \sum_{i=1}^{n} (P_i x S_i x F_i x C_i) \tag{4}$$

where n is the number of bank stocks in the basket; P_i is the price of bank i; S_i is the shares outstanding of bank i; F_i is the free-float rate of bank stock i; and C_i is the limited coefficient of capitalization weight of bank stock i in the index basket at the calculation time.

GSVI is released at the weekend so that investors will have a rational reaction at the first trading date of the week (Bijl et al. 2016; Swamy and Dharani 2019). Therefore, the first opening price is chosen to measure GSVI.

Research model

After reviewing the studies conducted by Kou et al. (2021a, b), Li et al. (2022), and other researchers in the field of finance, various approaches have been identified for estimating and predicting changes in the variables within the context of finance research in the digital era. These approaches offer diverse perspectives for gaining insights into the relationships between variables in this domain. However, in this study, we formulate seven time series models to explore the relationship between fintech and bank stock returns, elucidating the relationship between bank stock returns and all fintech variables based on the acquired data and the research objective.

$$\text{Model 1 (particular)} : \text{BankReturn} = \text{f(FinFintech)} \tag{5}$$

$$\text{Model 2(particular)} : \text{BankReturn} = \text{f}\left(\text{FinPayment}\right) \tag{6}$$

$$\text{Model 3(particular)} : \text{BankReturn} = \text{f}\left(\text{FinLending}\right) \tag{7}$$

$$\text{Model 4(particular)} : \text{BankReturn} = \text{f}\left(\text{FinMoney}\right) \tag{8}$$

$$\text{Model 5(particular)} : \text{BankReturn} = \text{f(FinWallet)} \tag{9}$$

$$\text{Model 6(particular)} : \text{BankReturn} = \text{f(FinProduct)} \tag{10}$$

$$\begin{aligned}\text{Model 7 (all)} : \text{BankReturn} &= \text{f(FinFintech, FinPayment, FinLending,}\\ &\quad \text{FinMoney, FinWallet, FinProduct)}\end{aligned} \tag{11}$$

Data analysis

In this study, a set of quantitative techniques—VAR-Granger and copula, are employed to estimate the relationship between fintech development and bank stock returns.

VAR-Granger is used to examine the relationship between time series variables and the reasons behind it. There are several reasons for employing VAR-Granger in this analysis. First, it helps in understanding and forecasting the relationship between the time series variables under investigation. Second, the series themselves and their lagged values may have an impact on each other. Third, VAR-Granger is suitable for both bivariate and multivariate time series analyses. In this study, fintech is considered as the exogenous series in relation to bank stock returns and vice versa. Based on the proposed models, VAR-Granger is deemed highly appropriate for the analysis. The results obtained from the VAR-Granger estimation will provide insights into whether there exists a bidirectional or unidirectional causality between the pair of variables, thus shedding light on the relationship between fintech (measured by Google search) and bank stock returns.

Let us start with a simple case between two-time series X and Y modeled in a VAR(q). The Granger model will be as follows:

$$\begin{cases} Y_t = \alpha_1 + \sum_{i=1}^{q} \beta_i Y_{t-i} + \sum_{i=1}^{q} \gamma_i X_{t-i} + \mu_t \\ X_t = \alpha_2 + \sum_{i=1}^{q} \delta_i Y_{t-i} + \sum_{i=1}^{q} \theta_i X_{t-i} + \sigma_t \end{cases} \tag{12}$$

Depending on the statistical value of γ and δ, four types of Granger causality between X and Y are determined as follows:

- If $\gamma \neq 0$ and is significant and δ is insignificant, X causes the change in Y (unidirectional)
- If γ is insignificant and $\delta \neq 0$ and is insignificant, Y causes the change in X (unidirectional)
- If $\gamma \neq 0$ and is significant and $\delta \neq 0$ and is insignificant, there is causality between X and Y (bidirectional)
- If γ is insignificant and δ is insignificant, there is no causality between X and Y.

The copula method is an effective approach used to determine joint distribution based on the dependence structure of variables, and it has gained popularity in the field of finance (Aas 2016; Patton 2012; Rodriguez 2007). To the best of our knowledge, no study has examined the application of the copula approach in the fintech literature, particularly when investigating the relationship between banks and fintech. Therefore, we contend that utilizing copula to estimate the relationship between fintech and bank stock returns is necessary to contribute new scientific evidence in this emerging area. Furthermore, there are specific reasons for employing the copula approach in this study. First, employing it together with VAR-Granger enhances the estimation process, facilitating a comprehensive empirical analysis. Second, it allows for the determination of the dependency structure, encompassing left-tailed, right-tailed, and normal distributions between variables. By incorporating the copula approach, a more comprehensive understanding of the relationship between fintech and bank stock returns can be achieved.

The three famous families of copula are Gumbel, Clayton, and Gaussian (normal), which are powerful in estimating the dependency structure between pair time series variables by the right-tail, left-tail, and normal distribution, respectively (Hofert et al. 2018;

Huynh et al. 2020). The Gumbel approach captures the right-tail (or upper-tail) dependency, which means pair variables might have simultaneous positive changes. In contrast, the Clayton approach indicates the simultaneous negative changes of pair variables or the left-tail dependency (or lower-tail). The Gaussian approach reveals the no-tail dependency structure between pair variables. This study employs three approaches to estimate the dependency structure between variables. The maximum pseudo-likelihood method is employed to estimate the parameters of the Gumble, Clayton, and Gaussian approaches.

There is one copula if all x, y ϵ [− ∞, + ∞], which is F(x, y) = C(FX(x), FY(y)), with F(x, y) is a joint density function with margin function F(X) and F(Y). Following Jin (2018), the parameters and structure dependence are estimated, as presented in Table 3.

Furthermore, the Kendall-plot graphic provides the visual diagnosis, which is also used for assessing the dependency structure between pair variables (Hofert et al. 2018; Huynh et al. 2020), as follows:

The data are arranged by quantile–quantile-plot (QQ-plot) for testing the normal features. The data (X_i, Y_i) are converted into (W_i:n, H(i)) with i = 1, 2, …, n.

The value of H(i) is followed by:

$$W_i : n = \omega k_0(\omega)\{K_0(\omega)\}^{i-}\{1 - K_0(\omega)\}^{n-i} d\omega \tag{13}$$

With H(i) < … < H(n), and $W_i : n$ is the expected statistical value in ranking i from the random sample W = C(U,V) = H(X,Y) with n observations. The value of W_i:n is calculated as follows:

$$K_0(\omega) = P(UV) \leq \omega = P\left(U \leq \frac{\omega}{v}\right)dv = 1dv + \frac{\omega}{v}dv = \omega - \omega log(\omega) \tag{14}$$

where k_0 is the relative density.

Moreover, before using the VAR-Granger and copula to estimate the relationship between time series variables, the Dickey–Fuller and Phillips–Perrons approaches are first used to check the stationary of data series or unit root test. If the data series are not stationary at level I(0), the first difference will be an alternative. Next, the optimal lags of the variables are selected (Lütkepohl 2005). Then, the co-integration test is performed to check the short- and long-run relationship between the variables (Dolado et al. 1990; Pfaff 2008).

Table 3 Copula estimation of parameters and structure dependence

Name	Copula	Parameter	Structure dependence
Gaussian	$C_N(u, v, \rho) = \varnothing(\varnothing^{-1}(u), \varnothing^{-1}(v))$	ρ	No tail dependence:$\lambda_U = \lambda_L = 0$
Clayton	$C_C(u, v, \theta) = C_C(1 - u, 1 - v; \theta)$	θ	Asymmetric tail dependence: $\lambda_U = 0, \lambda_L = 2^{-1/\theta}$
Gumbel	$C_G(u, v, \delta) = \exp(-\left((-\log(u))^\delta + (-\log(v))^\delta\right)^{1/\delta})$	$\delta \geq 1$	Asymmetric tail dependence: $\lambda_U = 2 - 2^{1/\delta}, \lambda_L = 0$

Source: Jin (2018)

Table 4 Descriptive statistics and unit root test

Variable	Obs	Mean	Std. Dev	Min	Max	Dickey–Fuller test	Phillips–Perron test
BankReturn	209	0.0020713	0.0378595	−0.1315444	0.1301236	−12.004***	−12.055***
FinFintech	209	0.3393684	0.1807558	0	1	−12.433***	−12.508***
FinPayment	209	0.3462506	0.1760233	0	1	−12.200***	−12.333***
FinLending	209	0.1839054	0.1022469	0	1	−13.013***	−13.110***
FinMoney	209	0.4098034	0.1475019	0	1	−12.494***	−12.772***
FinWallet	209	0.3462138	0.1820644	0	1	−12.358***	−12.465***
FinProduct	209	0.4271674	0.145622	0	1	−12.815***	−12.999***

*, **, and *** are significant at the 10%, 5%, and 1% levels, respectively

Source: The Authors

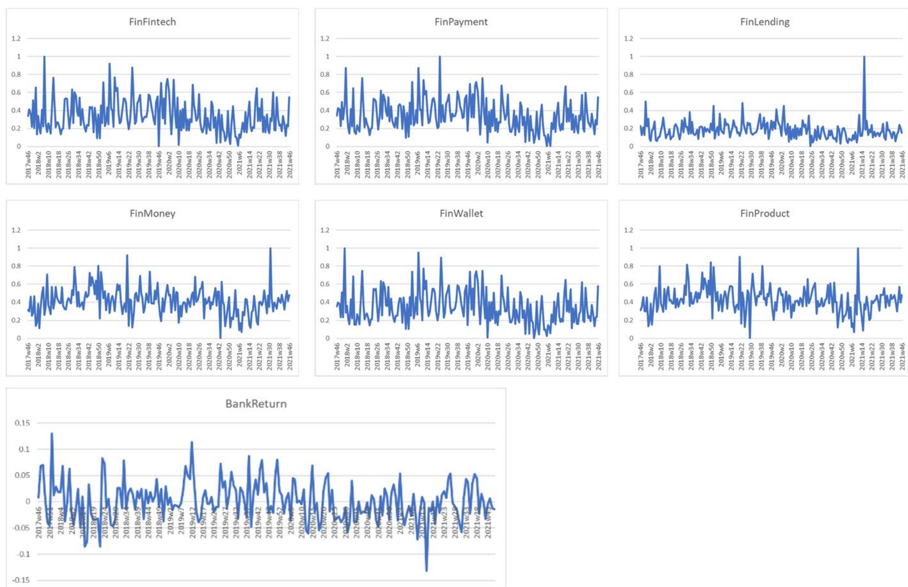

Fig. 1 Kendall-plot graphics

Results and discussion

Descriptive statistic and unit root test

The characteristics of the variables are presented in Table 4 and Fig. 1. There are 209 observations, which are the weekly data from 2017w46 to 2021w47. $\text{BankReturn}_{\text{mean}}$ indicates that the average return of 8 banks is 0.0020713 (about 0.2%/week). $\text{BankReturn}_{\text{min}} = -0.131544$ and $\text{BankReturn}_{\text{max}} = 0.1301236$, implying that investors can lose and gain the largest return at approximately 13.15% and 13.01%, respectively. We argue that they are very risky, which is consistent with the views of Batten and Vo (2016) and Dang (2019) that the volatility of bank stock return in Vietnam is high.

The means of fintech variables indicate that the highest searching volume keyword is the product ($\text{FinProduct}_{\text{mean}} = 0.4271674$), followed by the money, payment, wallet, and fintech in general, and the lowest is lending ($\text{FinLending}_{\text{mean}} = 0.1839054$). Based on these results and the component of variables, as presented in Table 2, it can be concluded that searching for fintech products is the priority of investors; after that, they seek information about the types of fintech products, such as money, payment, wallet, and lending. It also reveals an interesting finding that investors are less interested in the general keywords of fintech compared with keywords related to product, money, payment, and wallet.

Figure 1 indicates that the seven series are stochastic, and no shock affects the series movement; thus, the series period is appropriate for the next analysis without splitting.

Next, the graphical diagnostic of the movement of variables and the estimation results of the Dickey–Fuller test and Phillips–Perrons test indicate that all variables are stationary at the I(0) level. Therefore, the data series are eligible for further quantitative analysis.

Relationship between bank stock return and specific fintech variables

Choosing the optimal lags plays the most important role in the processing data series, especially for the VAR model estimation. Following Lütkepohl (2005), the main statistical values of the final prediction error, Akaike's information criterion, Hanna and Quinn information criterion, and Schwarz's Bayesian information criterion for choosing the optimal lags are estimated in Table 5. As weekly data are employed, if considerations of statistical values are not consistent, Akaike's information criterion is preferred for considering the optimal lags (Huynh 2019; Ivanov and Killian 2001; Nasir et al. 2019). Based on the results, the optimal lags of two (2) are selected for Models 1, 3, 4, and 5, and lags

Table 5 The lag-order selection of specific fintech models

Lag	Model 1. BankReturn = f(FinFintech)				Model 2. BankReturn = f(FinPayment)			
	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	0.000043	− 4.37101	− 4.3579*	− 4.33859*	0.000041	− 4.42685	− 4.41374	− 4.39443*
1	0.000043	− 4.38228	− 4.3429	− 4.28502	0.00004*	− 4.45815*	− 4.41882*	− 4.3609
2	0.000043*	− 4.3828*	− 4.31724	− 4.22071	0.00004	− 4.44685	− 4.38129	− 4.28476
3	0.000044	− 4.35986	− 4.26806	− 4.13292	0.000041	− 4.41973	− 4.32794	− 4.19279
4	0.000045	− 4.32744	− 4.20943	− 4.03567	0.000043	− 4.39004	− 4.27203	− 4.09827
Lag	Model 3. BankReturn = f(FinLending)				Model 4. BankReturn = f(FinMoney)			
	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	0.000015	− 5.43138	− 5.41827	− 5.39896	0.000031	− 4.6932	− 4.68009*	− 4.66078*
1	0.000014	− 5.51814	− 5.4788	− 5.42088	0.00003	− 4.71116	− 4.67182	− 4.6139
2	0.000013*	− 5.60185*	− 5.53628*	− 5.43975*	0.000031*	− 4.71645*	− 4.65088	− 4.55435
3	0.000013	− 5.58547	− 5.49368	− 5.35853	0.000031	− 4.69841	− 4.6066	− 4.47147
4	0.000013	− 5.5752	− 5.45718	− 5.28342	0.000032	− 4.66419	− 4.54617	− 4.37241
Lag	Model 5. BankReturn = f(FinWallet)				Model 6. BankReturn = f(FinProduct)			
	FPE	AIC	HQIC	SBIC	FPE	AIC	HQIC	SBIC
0	0.000043	− 4.37561	− 4.3625*	− 4.34319*	0.000031	− 4.71639	− 4.70327*	− 4.68397*
1	0.000043	− 4.38616	− 4.34682	− 4.2889	0.00003*	− 4.73262*	− 4.6932	− 4.63536
2	0.000043*	− 4.38863*	− 4.32306	− 4.22653	0.00003	− 4.73154	− 4.66598	− 4.56945
3	0.000044	− 4.36674	− 4.27495	− 4.1398	0.000031	− 4.70196	− 4.61017	− 4.47502
4	0.000045	− 4.33774	− 4.21973	− 4.04597	0.000032	− 4.66663	− 4.54861	− 4.37485

of one (1) are chosen for Models 2 and 6. The selected optimal lags are used for the next analysis.

Next, following Dolado et al. (1990), Huynh (2019), Johansen (1988), Lütkepohl (2005), and Nasir et al. (2019), the error correction approach is used to estimate the co-integrating relationship between the pair variables of Model 1–6. The co-integration test is significant in determining the relationship between variables that persist in the short or long run. The estimation results in Table 6 indicate that the trace statistics are always higher than the 5% critical value in all ranks; thus, we can conclude that no pair variables persist in the long run. Therefore, the VAR estimation is preferred for assessing the relationship between fintech and bank stock return.

Based on the studies by Huynh (2019) and Nasir et al. (2019), the VAR-Granger approach is utilized to estimate the causal relationship between fintech and bank stock returns. The estimation results are presented in Table 7. The findings validate two bidirectional causalities between pair variables—BankReturn and FinPayment as well as BankReturn and FinLending. Additionally, two unidirectional causalities are observed—from BankReturn to FinFintech and from BankReturn to FinWallet. The impact of BankReturn on the volume of fintech searches is greater than the influence in the opposite direction. Specifically, BankReturn can be predicted by two variables (FinPayment and FinLending) and serves as a predictive factor for four variables (FinPayment, FinLending, FinFintech, and FinWallet). This confirms the relationship between bank stock returns and the volume of fintech searches, which is consistent with the findings in the studies by Buchak et al. (2018), Navaretti et al. (2018), Tang (2019), and Thakor (2020)

Table 6 The co-integration test of specific models

Model 1. BankReturn = f(FinFintech)					**Model 2. BankReturn = f(FinPayment)**				
Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% critical value**	**Rank**	**LL**	**Eigenvalue**	**Trace Statistic**	**5% critical value**
0	387.73811		152.2501	15.41	0	348.74483		241.3153	15.41
1	436.41076	0.37516	54.9048	3.76	1	421.5307	0.50335	95.7436	3.76
2	463.86315	0.23298			2	469.4025	0.36891		
Model 3. BankReturn = f(FinLending)					**Model 4. BankReturn = f(FinMoney)**				
Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% critical value**	**Rank**	**LL**	**Eigenvalue**	**Trace Statistic**	**5% critical value**
0	514.41508		151.8258	15.41	0	431.94114		132.0206	15.41
1	563.90943	0.38011	52.8371	3.76	1	472.62479	0.32502	50.6533	3.76
2	590.32797	0.22528			2	497.95142	0.21706		
Model 5. BankReturn = f(FinWallet)					**Model 6. BankReturn = f(FinProduct)**				
Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% critical value**	**Rank**	**LL**	**Eigenvalue**	**Trace Statistic**	**5% critical value**
0	388.51388		151.9807	15.41	0	380.70609		234.4007	15.41
1	437.52183	0.37719	53.9648	3.76	1	443.77956	0.45473	108.2538	3.76
2	464.50421	0.22949			2	497.90646	0.40575		

Source: The Authors

Table 7 Granger causality for pair variables in the specific models

Panel 7.1	BankReturn	FinFintech	Panel 7.2	BankReturn	FinPayment
BankReturn	–	5.298*	BankReturn	–	4.4872**
FinFintech	3.4975	–	FinPayment	2.8908*	–
Panel 7.3	**BankReturn**	**FinLending**	**Panel 7.4**	**BankReturn**	**FinMoney**
BankReturn	–	18.42***	BankReturn	–	0.6059
FinLending	23.696***	–	FinMoney	4.3291	–
Panel 7.5	**BankReturn**	**FinWallet**	**Panel 7.6**	**BankReturn**	**FinProduct**
BankReturn	–	6.3459**	BankReturn	–	0.25404
FinWallet	2.4163	–	FinProduct	2.4719	–

*, **, 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

Table 8 The lag-order selection and co-integration test of model 7 (total)

Panel 8.1. The lag-order selection					Panel 8.2. The co-integration test				
Lag	FPE	AIC	HQIC	SBIC	Rank	LL	Eigenvalue	Trace Statistic	5% critical value
0	5.4e−16	− 15.2966	− 15.2507	− 15.1831*	0	1430.9964		699.7386	124.24
1	3.8e−16	− 15.6509	− 15.2837	− 14.7432	1	1528.5637	0.61042	504.6039	94.15
2	2.3e−16*	− 16.1445*	− 15.4561*	− 14.4425	2	1611.7536	0.55236	338.2241	68.52
3	2.9e−16	− 15.9055	− 14.8958	− 13.4092	3	1658.7395	0.36490	244.2523	47.21
4	3.5e−16	− 15.7467	− 14.4158	− 12.4561	4	1702.5996	0.34542	156.5323	29.68
					5	1741.4048	0.31266	78.9219	15.41
					6	1765.9074	0.21080	29.9165	3.76
					7	1780.8657	0.13457		

*Is the suggestion of lag-order selection

Source: The Authors

regarding the relationship between banks and fintech in the digital era. However, most existing publications agree that fintech has a more substantial impact on banks than vice versa. Furthermore, the estimation results do not support the causality between BankReturn and FinProduct, as well as between BankReturn and FinMoney.

Furthermore, an additional noteworthy finding has emerged, that is, despite the highest volume of searches for the keywords of fintech products, no relationship is observed between searching for fintech products and bank stock prices. This phenomenon can be attributed to the curiosity of investors regarding fintech products. Investors may search for fintech products out of curiosity rather than utilizing the information as a reference for making investment decisions.

Relationship between bank stock return and total fintech variables

Furthermore, we consider the relationship between bank stock return and total fintech variables (*Model 7*). Table 8 indicates that lags of two (2) are suitable with Model 7, and the relationship between bank stock return and fintech variables does not persist in the long run.

The estimation results presented in Table 9 confirm the previously mentioned bidirectional causality between BankReturn and FinLending, indicating a significant relationship between the volume of searches for P2P lending and bank stock returns. The development of P2P lending platforms on the internet has resulted in more advanced lending products being offered by both fintech companies and traditional banks (Bachmann et al. 2011; Wan et al. 2016). The curiosity surrounding P2P lending products has contributed to the expansion of the credit market, which improves bank performance. Additionally, when bank performance is positively perceived, marketing campaigns are often initiated to increase the number of lending customers in the online space (Domazet and Neogradi 2019; van Thiel and van Raaij 2019). Based on our observations of the digital marketing campaigns of Vietnamese banks, particularly regarding e-loans, we argue that the bidirectional causality between BankReturn and FinLending aligns with the aforementioned reasoning. Table 9 does not provide evidence to support the existence of bidirectional or unidirectional causality from BankReturn to other fintech variables.

However, Table 9 reveals an interesting aspect. It appears that the participants are not solely searching for specific fintech categories. There is a significant influence of one fintech category on another, suggesting that searching for one fintech category may predict interest in others. Specifically, there is a unidirectional causality from FinFintech to FinLending, from FinPayment to FinLending and FinWallet, from FinMoney to FinFintech, from FinWallet to FinLending, and from FinProduct to FinFintech. We argue that these interconnections between fintech categories might serve as indicators for predicting the development of specific subsectors within fintech through search volume. For instance, after searching for information about fintech payment, users are likely to search for information about fintech lending and fintech wallets as these factors are associated with fintech payment.

Furthermore, our exploration reveals that FinLending maintains more relationships compared with the other fintech variables. The influences of FinFintech, FinPayment, and FinWallet on FinLending are supportive activities for the development of P2P lending. We argue that this is well-suited for the Vietnamese economy due to the following reasons. Vietnam is a developing country where people face constraints in accessing

Table 9 Granger causality for pair variables in model 7 (total)

Variable	BankReturn	FinFintech	FinPayment	FinLending	FinMoney	FinWallet	FinProduct	ALL
BankReturn	–	1.9395	0.15928	16.096***	1.2721	2.4653	1.1427	28.882***
FinFintech	3.3195	–	1.8912	156.67***	2.9112	3.9989	0.75953	179.51***
FinPayment	3.5353	0.84315	–	127.93***	2.1413	7.5292**	0.80516	152.71***
FinLending	25.61***	0.49132	0.91805	–	3.7406	0.47894	1.5426	38.559***
FinMoney	2.7433	9.7181***	1.555	1.8949	–	2.7632	2.1868	23.438**
FinWallet	2.2384	0.63603	3.1008	168.83***	2.2134	–	0.62177	191.63***
FinProduct	2.9429	11.781***	2.0084	0.35991	0.1992	3.2744	–	24.218**

*, **, 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

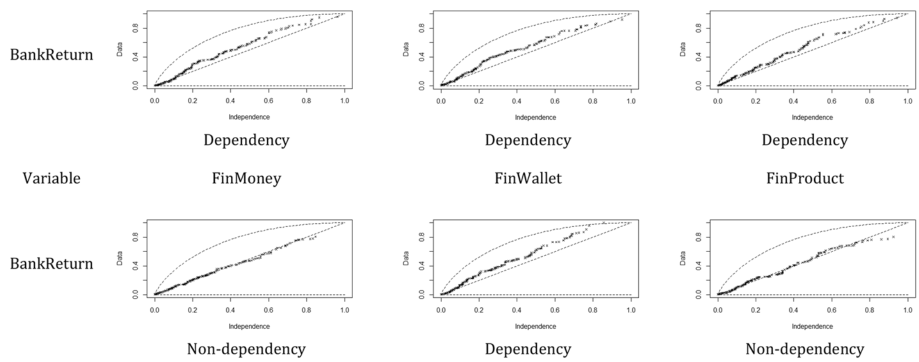

Fig. 2 Kendall-plot graphics illustrating the dependency structure among pair variables. Source: The Authors

Table 10 Estimated parameter and loglikelihood results by the three copula approaches

		BankReturn and FinFintech	BankReturn and FinPayment	BankReturn and FinLending	BankReturn and FinWallet
Clayton	Parameter	13.1362	2.1091	10.7072*	7.9939
	Log-likelihood	7.897	10.22	3.131	7.622
Gumbel	Parameter	1.205	1.217	1.1	1.222
	Log-likelihood	7.842	7.568	2.223	10.15
Normal	Parameter	0.2892*	0.3237*	0.1408	0.3058***
	Log-likelihood	8.429	10.71	1.915	9.486

(*) is considered the fittest estimation

Source: The Authors

traditional credit through front-of-desk transactions (Archer et al. 2020; Duy et al. 2012; Le 2012). Therefore, P2P lending platforms provide opportunities for borrowers to access credit and serve as a new investment channel for savers (Bachmann et al. 2011; Feng et al. 2015).

Copula estimation

As mentioned earlier, the estimation results obtained from VAR-Granger are further confirmed through copula estimation, which serves as a robustness check for the relationship between fintech and bank stock returns. Figure 2 depicts the Kendall plot graphic, which is utilized to visually analyze the interrelationship between the pair of variables. In the case of two pairs of variables, BankReturn and FinMoney, as well as BankReturn and FinProduct, a non-dependency structure is observed as the defined points align with the 45-degree line. This suggests that there is no structural dependence between these variables. Conversely, for the remaining four pair variables, namely BankReturn–FinFintech, BankReturn–FinPayment, BankReturn–FinLending, and BankReturn–FinWallet, a structural dependency is identified as the defined points deviate from the 45-degree line.

Next, based on the earlier graphical analysis, the tail dependence of the four pairs of variables is validated by estimating the parameter and log-likelihood values using

Clayton, Gumbel, and normal copula, as presented in Table 10. According to Embrechts (2009) and Huynh et al. (2020), copula approaches generally pass the goodness-of-fit test with a high success rate of approximately 99.9%. Therefore, the copula with the highest log-likelihood value is the best fit for determining tail dependency. Table 10 reveals that the structural dependence between BankReturn and FinLending exhibits a left-tail, indicating that in cases of a simultaneous decrease in bank stock price and the volume of searches for fintech lending keywords, the likelihood is higher compared with other scenarios. Furthermore, the three remaining pairs of variables (BankReturn–FinFintech, BankReturn–FinPayment, and BankReturn–FinWallet) have a normal shape, meaning that the probability of simultaneous increase or decrease between these pairs of variables is equal.

The copula estimation results confirm a significant relationship between BankReturn and FinLending. However, this relationship appears to be more pronounced in the case of downward movements than upward movements. This can be attributed to investors' preferences for bank stocks and their habit of searching for lending-related keywords on Google. When the volume of searches for fintech lending decreases, it implies that investors have reduced their income expectations from banks, thereby impacting the performance of bank stocks. Additionally, the decrease in the interest of investors in searching for information related to fintech lending indicates a lack of enthusiasm toward bank stocks. This implies that investors are seeking alternative opportunities in other types of stocks. Moreover, as previously mentioned, interest income forms a significant proportion of Vietnamese banks' earnings. Hence, a decline in bank stock returns signals a decrease in interest income, which alters investor behavior in terms of searching for fintech lending information.

The estimation results from multiple approaches reveal the existing relationship between fintech-related keyword searches and bank performance, indicating both positive and negative relationships. This confirms that fintech presents both opportunities and threats for banks, aligning with the arguments made in previous studies, such as those by Elsaid (2021) and Suryono et al. (2020). Fintech supports the scaling up of bank businesses by enhancing technology and reducing operational costs (Lee et al. 2021; Ruhland and Wiese 2022). However, fintech also offers advanced products that meet customers' requirements in the digital era, posing a significant challenge to banks. Particularly, fintech companies' retail financial products are highly appreciated for their cost, convenience, and user experience than those offered by traditional banks. Agarwal and Zhang (2020) and Omarini (2018) stated that fintech has disrupted the traditional market of commercial banks in payment and lending, necessitating suitable adaptation strategies by banks to cope with the rise of fintech. Many previous studies, such as those by Enriques and Ringe (2020) and Fang et al. (2022) have revealed that collaboration between banks and fintech is the optimal strategy for both entities and consumers in reshaping the financial landscape. Fintech companies bring innovation, agility, and technology-driven solutions to the table, while banks offer stability, regulatory compliance, and customer trust. This collaborative approach allows banks to leverage fintech expertise and technological advancements to enhance their services and remain competitive. Moreover, fintech companies gain access to the established customer base and regulatory frameworks provided by banks. Together, they can create a more seamless and inclusive financial ecosystem, benefiting all stakeholders involved.

Conclusions

Given the rapid growth of fintech in the digital era and the ongoing debate surrounding the relationship between fintech and banks, our objective is to investigate and enhance our understanding of this relationship in Vietnam, where the fintech industry has experienced significant growth. In addition, by reviewing existing quantitative research on fintech and bank performance, we observe that there is a variety of measures for the fintech variable, but the application of Google search as a measurement tool for fintech appears to be uncommon. We argue that this is a research gap that needs to be addressed to provide a novel approach to fintech measurement. Google search is a powerful tool for capturing contemporary issues in cyberspace, including investor attention toward fintech. Given the established relationship between investor attention measured by Google search and stock market indices, we employ time series models to estimate the relationship between fintech and bank stock returns. Considering factors such as lag effects in time series, the influence of exogenous variables, and the dependency structures between series, we suggest utilizing the VAR-Granger and copula approaches for estimating the relationship between fintech (measured by Google search) and bank stock returns.

The study reveals several significant findings. First, both the VAR-Granger and copula estimations indicate a significant relationship between bank stock returns and fintech lending, with the relationship being more pronounced during simultaneous negative changes. Second, the various estimation results suggest that the impact of fintech search volume on bank stock returns is weaker compared with the opposite direction, indicating that changes in bank stock returns attract investors' attention toward fintech. Third, the presence of unidirectional causality between fintech variables suggests that investors are not only focused on specific aspects of fintech but also exhibit curiosity by searching for various fintech topics in the online space. For example, after exploring general fintech subjects, investors tend to delve into specific areas such as fintech lending and fintech wallets. Additionally, they show interest in fintech payment systems after gaining knowledge about the broader fintech landscape. Similar patterns are observed for other types of fintech, such as from FinMoney to FinFintech, from FinWallet to FinLending, and from FinProduct to FinFintech. Furthermore, the findings indicate that the probability of simultaneous increase or decrease between bank stock returns and different fintech categories is equal. Specifically, the dependence structure of BankReturn and FinPayment, BankReturn and FinLending, as well as BankReturn and FinWallet follows the normal copula.

Based on these findings, several important policy implications can be drawn for stakeholders. First, the search volume of fintech lending, fintech payments, and fintech wallets can serve as predictive factors for bank stock returns, and investors should consider these factors when making investment decisions. Investors must exercise caution when there is a simultaneous decrease in bank stock returns and an increase in search volume for fintech lending. Second, the relationship between bank stock returns and the search volume of fintech-related keywords is weak, suggesting the need for further research to enhance our understanding of this relationship. Nevertheless, these findings should serve as valuable references for formulating policies related to bank stock trading in the exchange market. Lastly, for chief executives of Vietnamese banks, understanding the influence of fintech-related keyword search volume on bank stock returns is an important consideration in developing adaptation strategies for commercial banks in the context of the growing prominence of fintech.

Based on these arguments and the context of fintech and banking in Vietnam, we recommend fostering collaboration between fintech companies and banks as a suitable strategy. This approach not only brings numerous benefits for both entities but also for customers and the finance industry as a whole. The weaknesses of one party can be addressed by the strengths of the other, creating a mutually advantageous relationship. In this study, the increased presence of fintech sectors indicates a positive signal for banks in the stock market, while positive bank performance is closely linked to increased attention to fintech in the digital space. This connection will likely lead to an increase in the usage of fintech products provided by both fintech companies and banks.

The study contributes new empirical evidence to enrich our understanding of the relationship between bank performance and fintech information search in the digital era. It confirms the significant role of fintech in bank performance, establishing both positive and negative relationships. Building on these findings, further research can deeply categorize and investigate the relationship between specific segments of fintech and banks to provide clearer insights into their relationship. Additionally, in terms of practical contributions, the study demonstrates the capability of using Google search to measure fintech variables. It also applies VAR-Granger and copula methods to estimate the relationship between bank stock price and the volume of fintech-related keyword searches. These approaches can be utilized for further research in other markets to strengthen the relationship between fintech search and bank stock returns.

The study possesses certain limitations that provide avenues for further research in this field. First, the investigation into the relationship between fintech search volume and bank stock returns is conducted solely within Vietnam, an emerging country. Future studies can expand the scope by incorporating a cross-country analysis, particularly focusing on other emerging countries in Asia, where the fintech industry has experienced substantial growth in recent years. This will provide a broader perspective on the relationship between fintech and bank stock returns. Second, while the study employs VAR-Granger and three types of copulas (Gumbel, Clayton, and normal), other effective approaches can be used to estimate the relationship between bank stock returns and fintech search volume. These include ordinary least squares, ARIMA, ARCH/GARCH, and other branches of copula (e.g., Frank and Plackett). Future researchers may explore the application of these alternative approaches to gain further insights into the relationship under investigation. By addressing these limitations and incorporating additional methodologies, future studies can contribute to a deeper understanding of the complex dynamics between fintech, search volume, and bank stock returns.

Abbreviations

AGSVI	Average Google search volume index
GSVI	Google searching volume index
M&A	Merger and acquisition
P2P	Peer-to-peer
VAR	Vector autoregression
VAR-Granger	Granger causality and vector autoregression

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Author contributions
TPP: Idea, Data curation, Conceptualization, Writing—original draft, Visualization, Methodology, Formal analysis. DP: Conceptualization, Visualization, Methodology, and Revision. BP: Conceptualization, Visualization, Methodology, and Revision. SDH: Data curation, Writing—original draft, formal analysis. HTH: Data curation, Writing—original draft, formal analysis. All authors read and approved the final version of the manuscript.

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Availability of data and materials
We confirm that data will be available on reasonable request.

Declarations

Competing interests
We declare that we have no competing interests.

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