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Impact of Fintech's Development on Bank Performance: An Empirical Study from Vietnam

Phat Tien Pham[a], Ba Tri Tran[a], Thai Hoc Huynh[b], Boris Popesko[c], Duc Sinh Hoang[d]

[a]Can Tho University, Vietnam
[b]Van Lang University, Vietnam
[c]Tomas Bata University in Zlin, Czech Republic
[d]National University in Vietnam, Vietnam

Abstract: In recent years, fintech has exploded in popularity and importance in the financial industry. Its impacts have spread widely throughout the world, including Vietnam. This study aims to investigate the effect of fintech's development on bank performance in Vietnam. Based on the unstructured data about fintech on the financial expert websites from Vietnam, the word frequency statistic technique of the text mining approach is applied for measuring fintech's development under the support of Python-based solutions. The bank-level data of 15 Vietnamese banks for the period from the first quarter of 2019 to the second quarter of 2021 are collected from the quarterly financial statements in the Vietstock organization. Python programming and text mining techniques are used to compile this dataset by gathering information from popular and relevant websites. The generalized least squares method is used for estimating the panel models. The estimation result shows the significant impact of fintech's development on bank profitability, but the net interest margin does not associate with the fintech variable. Besides, some interesting findings are revealed: The slow banking transformation to adapt to the rise of fintech and the COVID-19 pandemic increased bank profitability. Furthermore, suggestions for the banks and fintech companies are recommended, and the limitations and directions for further research are also proposed.

Keywords: fintech, bank performance, text mining, Vietnam
JEL Classification: G21, O30

*Corresponding author's e-mail: pptien@ctu.edu.vn

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Introduction

In this digital era, technology seems to stick significantly to all aspects of social economics. The digitalization movement of governments and entrepreneurs is firmly going on all over the world. Technology companies are changing customers' behavior in various sectors, such as Uber in personal transportation, Airbnb in hospitality, Amazon in e-commerce, etc. Since 2008 to 2009 (the global financial crisis), the finance industry has significantly influenced disruptive technologies, formulating a new sector called fintech (Arner et al., 2015). Investigating the relationship between fintech and traditional financial institutions has attracted many scholars. For example, fintech plays an essential role in finance (Milian et al., 2019). According to Thakor (2020), the banking industry is being shaped by fintech's development, which significantly impacts fintech's development on bank credit (Sheng, 2021). By contrast, fintech negatively impacts a bank's performance (Phan et al., 2020). Consequently, the effect of fintech on a bank is still debatable, which needs more empirical studies to examine the relationship between fintech and bank performance.

Based on the perspective of quantitative research about measuring fintech, there might be various ways of measuring the fintech variables. For example, Phan et al. (2020) estimated the fintech variable as the number of fintech companies. Asmarani and Wijaya (2020) proposed that the fintech variables are fintech's funding frequency and fintech's funding value. Dranev et al. (2019) stated that the merger and acquisition of related firms in the fintech sector measured the fintech variable. However, those approaches might be outdated because a tremendous amount of information about fintech has been released into cyberspace. According to Xie et al. (2020), Li et al. (2020), and Gupta and Lehal (2009), the text mining approach might be appropriate to mine the unstructured data from the Internet. Therefore, it should be considered to be a new method to measure fintech's development through mining unstructured data about fintech in cyberspace. The text mining technique and Python-based crawling data are proposed in this study.

There is a significant impact from the released information on firm performance in finance. Leung and Ton (2015) found that the Australian stock market's internet message board significantly influences the stock return change. Based on the dataset from the Internet (social media, news articles, etc.), Audrino et al. (2020) stated that attention and sentiment significantly impact firm performance. Li et al. (2018) determined that increased released information significantly affects firm performance. Furthermore, the link between fintech and banks might be because they are competitors, or allies (Navaretti et al., 2018; Vives, 2019); thus, the information about fintech might influence bank performance. Those reveal that fintech might be measured by mining information on the Internet, which boosts research investigating the effect of fintech on bank performance.

Consequently, this paper investigates the relationship between fintech and bank performance in developing countries, where fintech plays the most crucial role in providing financial products to non-account banking users. Vietnam is an ideal case study to conduct this study. There is a massive amount of information about fintech in cyberspace in Vietnam, especially on the specific websites of the finance market, which might be used to evaluate the development of fintech. The text mining approach might be an effective tool for collecting and analyzing relevant issues on the Internet. Besides, we explore and find that studies about measuring fintech variables using the text mining approach seem to be rare. Therefore, these all lead to the argument that there is a research gap, and it needs to be filled.

The rest of this study consists of the literature review section about applying the text mining approach in the finance industry, and the link between fintech and bank performance. The methodology section is about the fintech index measurement and research model. The results and discussion are presented in Section 4, and sections 5 and 6 are the conclusion and limitation.

Literature Review

This study will add the fintech variable into the determinant of the bank performance model to investigate the impact of fintech on bank performance. Therefore, there are two main sub-sections in this section. The first section presents the articles relevant to the determinant of bank performance, and the second illustrates the relationship between fintech and bank performance. Moreover, empirical studies of the text mining approach to measuring the variable through mining unstructured data from cyberspace are proposed as the background for fintech's measurement. The Vietnamese fintech context is also presented in this section.

Vietnamese fintech context

Vietnam presently has around 200 fintech companies that provide a wide variety of services ranging from digital transactions to financial services, peer-to-peer lending, and blockchain-based solutions. The emergence of Vietnam's fintech ecosystem is changing the whole financial sector, seizing areas that were previously untapped by conventional banking and garnering a lot of interest from foreign investors. Vietnam's fintech business developed substantially from 39 enterprises in 2015 to 112 in 2017, 169 in 2019, and about 188 by September 2021 (Tracxn and UOB, 2021). Digital payments, peer-to-peer (P2P) lending, cryptocurrencies and blockchain, investment tech, and point of sale are the major sub-sectors in Vietnam, accounting for 76% of the overall fintech market share. The increase in investment, in both value and size, demonstrates the appeal of Vietnam's fintech sector. According the report "Fintech in ASEAN 2021: Digital takes flight" by UOB, PwC, and SFA, Vietnam received 15 investment transactions between January and September 2021, putting the nation in a tie for third place with Malaysia, after Singapore and Indonesia. In addition, the nation placed third in fintech transaction value in 2021, with 375 million USD invested, accounting for 11% of the overall transaction amount in ASEAN-6 2021.

Determinant of bank performance

Investigating the relationship between the capital and earnings of US banks in the 1980s, Berger (1995) explored the positive effect of capital on earnings. The author explained that higher capital increases bank profits by decreasing interest expenses. Besides, a capital increase is a positive signal of bank performance. Based on data from 44 Islamic banks in Asia and Africa in 2013, Chowdhury and Rasid (2015) stated that, through the safeguard of depositors in the case of the chaos of macroeconomics, the increase in capital would enhance bank performance. On the other hand, in a survey of the U.S. banking sector from 1976 to 2010, Osborne et al. (2012) explained that due to the expense of capital being higher than debt, there is a negative impact of a capital factor on bank performance. However, most scholars agree that the capital factor positively influences bank performance such as Al-Matari (2021) and Batten and Vo (2019). Therefore, in this study, we expect the estimation result to be consistent with most of the existing findings.

Al-Matari (2021) found a negative relationship between bank size and bank performance in Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates from 2000 to 2008. The author explains that this is due to the increased management costs and the bureaucratic issues of a large bank, compared with those of a small bank. This is similar to the findings of Batten and Vo (2019) and Menicucci and Paolucci (2016). On the other hand, the large-sized banks will be more economically advanced than the small-sized banks, namely with their banking products' diversification and extended branches. The positive effect of bank size on bank performance is found in the study by Pham et al. (2021) in Vietnam and Pakistan from 2011 to 2019, and by Phan et al. (2020) in Indonesia. Besides, Ali and Puah (2019) discussed that a strong brand name image and market power are the advanced factors of large-sized banks that help enhance their performance in Pakistan. In this study, we choose Vietnam, a developing country like Indonesia and Pakistan; thus, we expect a positive effect of bank size on bank performance.

The main functions of commercial banks are to receive money from depositors and issue loans to borrowers, especially in developing countries; thus, we consider that these two functions are significant factors of a bank's performance, namely its profitability. Covering the data from June 1990 to March 2011 in Colombia, Amador et al. (2013)

stated there was a positive relationship between bank risk and the growth of loans, which increases non-performing loans and reduces solvency. Thus, we argue that loan growth is a negative factor in bank performance, especially profitability. However, from the second quarter of 2002 to the fourth quarter of 2013, Niu (2016) linked fast loan growth to higher bank performance in the USA. Another study by Dang (2019) about the relationship between loan growth and the performance of 31 commercial banks in Vietnam from 2006 to 2017 explored the positive effect of the short-term and long-term growth of loans on bank profitability. In this study, we argue that the primary income of commercial banks is from credit products; thus, the growth of loans leads to increased bank income. In contrast with the business of issuing credit, banks must factor in the expense of interest cost to raise capital, which means a growth in deposits leads to increased bank expenses and decreased bank profit. Consequently, we expect a positive effect of loan growth, and a negative impact of deposit growth, on bank performance.

Relationship between banks and fintech

The association between banks and fintech is reflected in explicit and implicit quantitative and qualitative studies. On the side of qualitative research, Vives (2017, 2019) stated that fintech is a significant factor that changes the structure and enhances the efficiency of the banking sector. Another study by Ozili (2018) showed three ways that fintech has an effect on banks, namely a positive effect, an adverse effect, and two-way causality. Fintech supports a bank in extending its banking products' list, especially the products' links to technology platforms. However, fintech is a new competitor for the banks; thus, the banks' market share in the finance market might be getting smaller, which negatively influences bank profitability. Besides, Ozili (2018) also said that the link between fintech and banks might be affected by other factors, such as macroeconomics, bank characteristics, and time series. Moreover, in agreement with the view of Alt et al. (2018), Lee and Shin (2018), and Thakor (2020), we consider that the rise of fintech seems to be more advantageous than disadvantageous for the banks.

In a quantitative study, Phan et al. (2020) collected the number of fintech companies, macroeconomics, and internal bank characteristics from the Fintech Indonesia Association and Global Financial Database to survey the effect of fintech on bank performance in Indonesia. The estimation results showed a negative impact of fintech on bank performance. Besides, the authors explored that small-sized banks are more dynamic in adapting to the rise of fintech than large-sized banks are. However, using the monthly data from January 2016 to October 2018, Asmarani and Wijaya (2020) found no significant impact of fintech on the performance of Indonesian banks. On the other hand, Sheng (2021) provided that fintech helped increase credit for SMEs in China from 2011 to 2018.

Besides, Li et al. (2017) explored the positive relationship between fintech and bank stock returns in the USA. We argue that increasing credit and a good performance on the stock market are the requirements for increasing bank profits, especially in developing countries such as Vietnam.

Consequently, in this study, the hypothesis is: *"There is a positive effect of fintech's development on bank performance."*

Text mining approach in finance

In the finance industry, the amount of data have risen immensely, especially unstructured data. Gupta et al. (2020) indicated the application of the text mining approach for three sub-sectors of the finance industry, namely financial prediction (e.g., stock market, forex market, etc.), banking (e.g., risk management, customer relationship, etc.), and corporate finance (sustainability analysis, fraud detection, etc.). Pejić Bach et al. (2019) revealed that the text mining approach is the current research trend in the finance industry. The vast amount of semi-structured and unstructured data on various sources, such as the Internet (e.g., websites, social media, email, etc.), and internal and external documents disclose many meaningful components for the financial institutions and other participants.

There are various text mining techniques, consisting of word frequency statistics, text classification, sentiment analysis, text clustering, etc. However, the word frequency statistic is the original technique of the text mining method, and it is appreciated for its ability to mine unstructured data in the finance and accounting domain (Gupta et al., 2020; Gupta & Lehal, 2009; Loughran & McDonald, 2016). Therefore, following the studies by Nair (2014) and Richardson (2019), we prefer to use the word frequency statistic technique and the Scrapy/BeautifulSoup-based technique for measuring the fintech variable.

Methodology

There are three parts to this section. First, we propose a model for estimating the effect of fintech on bank performance. The second part is the data of the study and the variables' measurement. Finally, the data analysis method is presented.

Estimation model

From the studies by Li et al. (2017), Pham et al. (2021), and Phan et al. (2020), these estimation models were formulated to investigate the impact of fintech's development on bank performance. First, the models of the determinant of bank performance were developed with and without the lag of one term of bank performance. Second, the fintech variable was added to the determinant models to estimate the impact of fintech's development on bank performance. The specific models are shown below:

$$PER_{i,t}=\alpha+\Sigma_{j=1}^{n}\beta_j DETER_{j,i,t}+\mu_i+\delta_{i,t}$$
$$PER_{i,t}=\alpha+\gamma PER_{i,t-1}+\Sigma_{j=1}^{n}\beta_j DETER_{j,i,t}+\mu_i+\delta_{it}$$
$$PER_{i,t}=\alpha+\Sigma_{j=1}^{n} n\beta_j DETER_{j,i,t}+\theta_1 FIN_t+\mu_i+\delta_{it}$$
$$PER_{i,t}=\alpha+\beta_1 PER_{i,t-1}+\Sigma_{j=1}^{n}\beta_j DETER_{j,i,t}+\theta_1 FIN_t+\mu_i+\delta_{it}$$
$$PER_{i,t}=\alpha+\beta_1 PER_{i,t-1}+\Sigma_{j=1}^{n}\beta_j DETER_{j,i,t}+\theta_1 FIN_t+\theta_2 FIN_{t-1}+\mu_i+\delta_{it}$$

Where, $PER_{i,t}$ and $DETER_{i,t}$ were the performance and determinant variables of bank i at the time t, respectively; FIN_t was the fintech variable at time t; α was the constant; β, γ, and θ were the coefficients of determinant, performance, and fintech variables, respectively; μ_i was the bank effect to cover the specific heterogeneity; and δ_{it} was time-varying across banks and over time. Eq.1 and Eq.2 were the determinant models of bank performance, whereas Eq.3, Eq.4, and Eq.5 were the models to estimate the impact of fintech on bank performance.

Data and variables

Vietnam was considered to be an empirical dataset for clarifying the hypothesis. There were several reasons why Vietnam was chosen as the case study in this paper. Firstly, Vietnam is an emerging country where fintech has played the most crucial role in providing products to non-account banking users (Demirguc-Kunt et al., 2018; Morgan & Trinh, 2020). Secondly, many fintech companies in Vietnam have grown and influenced bank performance. We consider this country to be an exciting case study to conduct the research.

According to the rule of the State Securities Commission of Vietnam, the listed banks must disclose their quarterly financial statements, and based on the data available, we collected the data of 15 commercial banks listed on the Vietnamese stock market. Besides, the fintech sector has been growing rapidly; thus, it was suitable to record fintech's development quarterly (Wang et al., 2021). Therefore, we considered that the quarterly data was appropriate to reflect the changes in bank performance and fintech's development.

According to news articles in Fintech Singapore[1], Nikkei Asia[2], and Statista (2021), since 2019, the fintech sector has been growing in Vietnam, especially with the rise of fintech startup companies. Therefore, we selected the beginning of 2019 to start collecting the data for this study.

Vietstock, a trusted statistical security company on the Vietnamese stock exchange,

[1] Accessed Sep 27th, 2021: https://fintechnews.sg/45354/vietnam/2020-fintech-vietnam-report-and-start-up-map/

[2] Accessed Sep 27th, 2021: https://asia.nikkei.com/Business/Business-Spotlight/Vietnam-emerges-as-Southeast-Asia-s-next-fintech-battleground

provided the listed banks' data. The text mining approach, supported by Python programming language, collected and analyzed the data for measuring fintech's development.

Fintech development variable

According to Chaudhari et al. (2020) and Malik and Rizvi (2011), web scraping uses web pages to retrieve valuable and desired information from the World Wide Web (WWW) via Hypertext Transfer Protocol (HTTP) or a web browser. Web scraping can be automated using a web crawler, which opens specified web pages through HTTP at regular intervals to collect data. The primary purpose of a web scraper is to collect information from the Internet for data analysis and interpretation.

BeautifulSoup in the Python library package for web scraping was created with the ability to scrape data without needing any web API (Nair, 2014; Richardson, 2019). It was utilized in this case for web scraping and text mining from web pages. Because scrapers are web page-focused, creating a general scraper was exceedingly tricky. Thus, a list of websites were described in the data, then targeted to obtain fintech and other relevant data, to gather as much data as possible.

The majority of information on a webpage is placed in paragraph tags (<p>) and header tags (<h1>, <a>), yet only those tags were targeted. The data contained within these tags were subsequently extracted using the BeautifulSoup function "find_all() and get_text()." After that, the data were compiled for data analytics and processing in the next step.

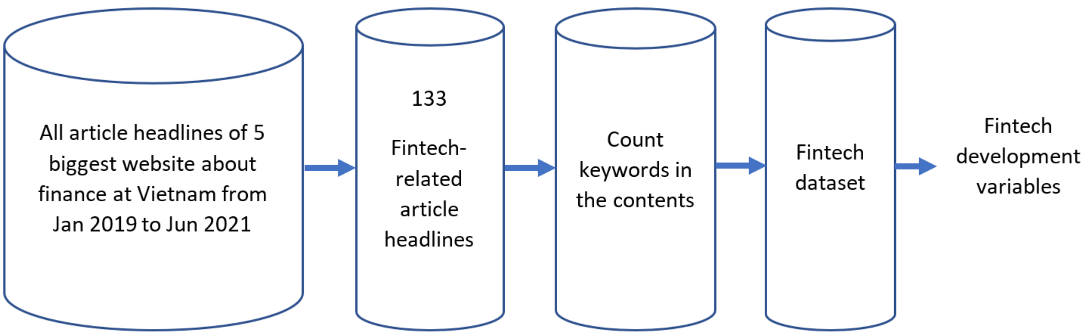

Figure 1. The obtaining fintech dataset process

In this study, we selected the top five largest websites[3], which happened to be the specialized news providers for the finance domain in Vietnam, to collect the data for quantifying fintech's development. The process to obtain fintech's development dataset is illustrated in **Figure 1**. For the first step, we adopted the BeautifulSoup package in Python to collected and analyze all the articles' headlines on the five most significant websites,

[3] Cafef.vn, TheSaigonTimes.vn, Nhipcaudautu.vn, CafeBiz.vn, and VnEconomy.vn

which were released between Jan 1, 2019, and Jun 30, 2021. Next, following the study by Cheng and Qu (2020), Pham et al. (2021), and Wang et al. (2021), we selected the articles which had the occurrence of the terms "fintech" or "Công nghệ tài chính[4]" (Academy of Finance, 2021). These keywords were highly appropriate to assess fintech's development in a specific country, like Vietnam. There were 133 selected articles, which were sorted by time. In the following stage, based on the content of the 133 selected papers, the terms "fintech" and "Công nghệ tài chính" were counted by using Scrapy/BeautifulSoup-based Python. Then, according to Fernández Del Carpio and Angarita (2018), in the regression estimation, the variable performance formulated by the data mining was guaranteed by the logarithm form. Consequently, in this study, fintech's development variable (FIN) was the number of "fintech" and "Công nghệ tài chính" occurrences on 133 fintech-related article headlines from the five biggest websites about finance in Vietnam, which were then transferred to logarithm form and sorted by quarter (from the first quarter of 2019 to the second quarter of 2021).

Bank performance and determinant variables

Following Batten and Vo (2019) and Phan et al. (2020), the bank performance variables were measured by the return on assets (ROA), return on equity (ROE), and net interest margin (NIM).

According to Batten and Vo (2019), Berger (1995), Pham et al. (2021), and Phan et al. (2020), the determinant variables conclude that:

- The logarithm of total assets measures bank size (SIZE). A giant bank is more advanced in its economies of scale and risk diversification than a small bank is; thus, the giant bank has higher operational efficiency and profitability than the small bank.
- Bank capital (CAP) is measured by the ratio of equity to total assets. Most previous studies agree that higher capital reduces interest expenses and increases expected profits. Besides, a capital increase regards the reduction of bankruptcy costs, a positive signal of bank prospects.
- Bank growth is measured by loan development (LOAN) and deposits (DEP) expansion. Loans and deposits involve interest income and expenses, respectively. However, credit activity is the primary function, which generally contributes to the most significant proportion of Vietnamese commercial banks' incomes (Batten & Vo, 2016; Vo, 2016); thus, the growth of loans and deposits plays a role in expanding the credit activities. Therefore, we argue that the development of loans and deposits is positive for bank performance.

The bank-level variables above are calculated based on the collected quarterly fi-

[4] Vietnamese form of term Fintech

nancial statements and annual reports. The characteristics of the variables are shown in **Table 1.**

Table 1. Descriptive statistic

Variable	Obs.	Mean	Std. Dev.	Min	25%	50%	75%	Max
ROA	150	0.0051966	0.0027039	0.000541	0.002586	0.005322	0.006841	0.0125016
ROE	150	0.0590618	0.0215071	0.005251	0.041969	0.061421	0.074205	0.1119945
NIM	150	0.0091336	0.003828	0.0039145	0.006511	0.00862	0.010458	0.0222673
SIZE	150	19.72825	0.7621073	18.42956	19.0367	19.75622	19.998384	21.21948
CAP	150	0.0853907	0.0294243	0.0411298	0.06386	0.078097	0.097379	0.1758782
LOAN	150	0.0450338	0.035749	-0.0131247	0.021141	0.042572	0.059082	0.2039747
DEP	150	0.0368467	0.0403501	-0.1172397	0.012176	0.034436	0.056807	0.1551734
FIN	150	6.430612	0.6255157	5.356586	6.006353	6.48948	6.747587	7.639161

Trading code of selected banks: ACB, BID, CTG, HDB, MBB, MSB, OCB, SHB, SSB, STB, TCB, TPB, VCB, VIB, and VPB

FIN had 10 values, and each bank's quarterly observation of fintech's development was repeated. FIN_{mean} was 6.430612, which showed the average popularity of fintech (the logarithm form of the number of “fintech” and “Công nghệ tài chính” occurrences) in the media compared with the sample period. The slight difference between FIN_{max} and FIN_{min} and small size of $FIN_{Sta.\ Dev.}$ showed that the level of fintech's popularity in the media was slightly changing. ROA_{min} and ROE_{min} were positive, which meant banks made a profit in the period. According to our knowledge about the banking sector, ROA_{mean} and ROE_{mean} were suitable for the Vietnam economy. NIM_{mean} was about 0.9%/quarter, which was consistent with many reports of the state of Vietnamese banks, the NIM of banks was about 3.5-4.0%/year. We explored that $LOAN_{mean}$ was larger than DEP_{mean}, and the growth of loans and deposits was negative in some quarters; thus, we were concerned that it might be a risk to banks in the future, especially the liquidity risk.

Analysis

Based on the strongly balanced panel, there were many ways to employ the five estimation models above, such as pooled, fixed-effect (FE), random-effect (RE), generalized least squares (GLS), and generalized method of moments (GMM) (Hansen, 1982). The pooled method considers the sample as cross-sectional data; thus, it was not suitable for the characteristic of panel data. The GMM method requires determining the endogenous and exogenous variables of the model (Wooldridge, 2001). However, Eq.1 and Eq.2 were endogenous variables (DETER variables) without exogenous variables (FIN variables), whereas Eq.3, Eq.4, and Eq.5 were both variables. Besides, we aimed to use the uniform method to process the five equations above; thus, we argue that the GMM method was unsuitable. We preferred the FE, RE, and GLS methods to meet our aim in this study.

The FE and RE methods were applied to estimate the effect of the independent variables on the dependent variable for the five equations. Then, the Hausman test was used to choose the proper estimation between the result of FE and RE (Hansen, 1982). After that, heteroskedastic and autocorrelation issues of the model were checked. The estimation results by FE or RE showed that all the models had heteroskedastic or/and autocorrelation; thus, the GLS method was used for fixing the issue(s) (Gujarati & Porter, 2009). Due to the limitation of page quantity, we could not present all the estimation results; thus, in this study, the estimation results by GLS are only suggested.

Results and Discussion

Table 2 shows the correlation between the variables and each variable's variance inflation factor (VIF). It is noticeable from this table that there was no evidence of multicollinearity for two reasons. The maximum absolute correlation value was 0.7860 (belongs to two dependence variables, ROA and ROE), which was less than 0.8 (Gujarati & Porter, 2009). Moreover, all five of the estimation models above had less than 10 explanatory variables, and the VIFmax (1.86) was smaller than VIFthreshold (4.00) (Gómez et al., 2020). Based on the results, we might have concluded that all the variables were eligible for the following stage of their analysis.

Table 2. Correlation and VIF

Variable	VIF	ROA	ROE	NIM	SIZE	CAP	LOAN	DEP	FIN
ROA	-	1.0000							
ROE	1.38	0.7860	1.0000						
NIM	1.86	0.6650	0.4578	1.0000					
SIZE	1.17	-0.2636	-0.1864	-0.0742	1.0000				
CAP	1.70	0.7708	0.2439	0.5697	-0.2805	1.0000			
LOAN	1.36	0.2740	0.2217	0.0656	-0.2373	0.2071	1.0000		
DEP	1.30	0.1336	0.1930	0.0696	-0.1683	0.0384	0.4390	1.0000	
FIN	1.02	0.0165	0.0610	-0.0232	-0.0227	-0.0275	0.0516	0.1381	1.0000

As we mentioned above, tables 3-4-5-6 show the estimation results by the GLS approach, which fixed the heteroscedastic and/or autocorrelation issues of the estimation results of the FE or RE approach. The critical statistic value (see row Sta. of tables 3-4-5-6) of all the models stated that all the models were significant at the1% level, which meant the estimation results were eligible to explain the effect of the independent variables on the dependent variable (Wooldridge, 2010).

The effect of fintech on bank performance

First, **Table 3** gives the estimation results of the effect of fintech on ROA. It can be seen that ROAt-1, CAP, and LOAN were significantly positive with ROA, while SIZE and DEP were not significant. Besides, we explored the positive effect of fintech (FIN) on the banks' return on assets in the sample period, but the lag of FIN was a negative sign.

Table 3. The effect of fintech on ROA

Variable	Model 1.1	Model 2.1	Model 3.1	Model 4.1	Model 5.1
ROA_{t-1}	-	0.7053288*** [11.80]	-	0.7036367*** [11.40]	0.7274693*** [11.74]
SIZE	-0.0002228 [-1.49]	-0.0001444 [-1.23]	-0.0002611 [-1.19]	-0.0001286 [-1.09]	-0.0001242 [-1.08]
CAP	0.0751407*** [17.97]	0.0222886*** [4.43]	0.0727877*** [12.81]	0.0226904*** [4.40]	0.0209538*** [4.09]
LOAN	0.0050971 [1.30]	0.0054889* [1.78]	0.0049932* [1.77]	0.0052809* [1.72]	0.0059484** [1.96]
DEP	0.0030946 [1.07]	0.0007769 [0.29]	0.0016919 [0.69]	0.0007288 [0.27]	-0.0008613 [-0.31]
FIN	-	-	0.0002893** [2.42]	0.0002962** [2.20]	0.0002802** [2.12]
FIN_{t-1}	-	-	-	-	-0.0002895* [-1.79]
Cons	0.0029001 [0.92]	0.0023972 [0.98]	0.0020739 [0.44]	0.0001371 [0.05]	0.0021111 [0.75]
Sta.	442.76***	1,028.69***	223.44***	995.43***	1,046.77***
N	150	135	150	135	135

Note:

- **, **, and *** means significant level at 10%, 5%, and 1% respectively*
- *FE and RE run all models; then, the Hausman test selects the proper estimation between FE and RE.*
- *The estimation results of FE or RE have heteroskedastic and/or autocorrelation; thus, GLS will fix the model.*

Second, the estimation result of fintech on ROE is given in **Table 4.** We also found the lag of ROE was a significant positive with ROE, but SIZE was a significant negative. In general, a higher CAP decreased bank profitability significantly, namely ROE. The fluctuation of LOAN and DEP were not substantial with ROE, which meant there was no evidence to conclude the dependency of ROE on the growth of loans and deposits. There was a significant sign of the FIN and FIN_{t-1} coefficients with ROE, like the above-mentioned relationship between fintech and ROA.

In this study, the significant effect of fintech on bank profitability (ROE and ROA) could be explained by the customers' attention to the amount of current "fintech" information on social media, which led to the changes in the demand to use banking products. Due to customer curiosity, fintech information led to an increased use of fintech products by banks (e.g., mobile banking products and online banking) and increased bank profits. However, we considered that information about fintech and the features of its products did not meet the customer's expectations; thus, the lag of FIN was negative with bank profitability. Another reason might be the implementation process for bankings' digitalization. The "boom" of fintech information on the Internet motivated the application of disruptive technologies (hardware and software) to reduce operating costs and increase profits. However, due to the update issues and information technology literacy, hardware and software investments might reduce the banks' profits (Beccalli, 2007).

Table 4. The effect of fintech on ROE

Variable	Model 1.2	Model 2.2	Model 3.2	Model 4.2	Model 5.2
ROE_{t-1}	-	0.7508411*** [13.71]	-	7.675617*** [9.08]	8.057131*** [9.33]
SIZE	-0.0053413** [-2.55]	-0.0026242 [-1.59]	-0.0050135 [-1.56]	-0.0043964** [-2.35]	-0.0043744** [-2.36]
CAP	0.1514731*** [3.34]	0.008929 [0.33]	0.1085117* [1.82]	-0.389654*** [-6.13]	-0.4162346*** [-6.48]
LOAN	0.0332861 [0.74]	0.0601888** [2.03]	0.0439937 [1.46]	0.0393835 [1.13]	0.0464632 [1.34]
DEP	0.0377793 [1.10]	0.0200279 [0.68]	0.0194141 [0.71]	0.0258061 [0.77]	0.0064692 [0.19]
FIN	-	-	0.0037806** [2.48]	0.0039573** [2.11]	0.0037178** [2.01]
FIN_{t-1}	-	-	-	-	-0.0041228* [-1.79]
Cons	0.1495321*** [3.47]	0.0642146* [1.87]	0.1232232* [1.85]	0.1128733*** [2.76]	.1417455*** [3.28]
Sta.	32.01***	247.94***	19.73***	123.42***	128.53***
N	150	135	150	135	135

Note:

- **, **, and *** means significant level at 10%, 5%, and 1% respectively*
- *FE and RE run all models; then, the Hausman test selects the proper estimation between FE and RE.*
- *The estimation results of FE or RE have heteroskedastic and/or autocorrelation; thus, GLS will fix the model*

The estimation results of the effect of fintech on NIM are shown in **Table 5.** There seemed to be a difference between the effect of fintech on NIM and the others (namely, ROA and ROE). There was no evidence about the relationship between fintech and NIM. The net interest margin did not depend on fintech's development or the amount of "fintech" information on social media. We argue that it was suitable for the current operation of commercial banks in Vietnam. The amount of information technology investment flows has gone to upgrade the payment products, rather than the credit products. Most mobile payment applications of commercial banks always have payment functions; credit functions are rare. Furthermore, the borrowers do not prefer to contact the bank via modern technologies and tend to do offline transactions.

Table 5. The effect of fintech on NIM

Variable	Model 1.3	Model 2.3	Model 3.3	Model 4.3	Model 5.3
NIM_{t-1}	-	0.9600714*** [48.71]	-	0.9599331*** [48.43]	0.9598841*** [48.66]
SIZE	-0.0000393 [-0.21]	-0.0000503 [-0.80]	-0.0000511 [-0.27]	-0.0000504 [-0.80]	-0.0000494 [-0.77]
CAP	0.0758773*** [9.83]	0.0036039 [1.22]	0.0753972*** [9.77]	0.0036304 [1.22]	0.0036896 [1.23]
LOAN	0.0052986 [1.00]	0.0039888** [2.05]	0.0049369 [0.93]	0.0039792** [2.04]	0.0039054 [1.99]
DEP	0.0031005 [0.76]	-0.0043769*** [-2.78]	0.0035788 [0.87]	-0.0043827*** [-2.77]	-0.0043572*** [-2.63]
FIN	-	-	-0.0001853 [-0.94]	4.16e-07 [0.00]	1.17e-06 [0.01]
FIN_{t-1}	-	-	-	-	-1.85e-06 [-0.02]
Cons	0.0031488 [0.77]	0.0012129 [0.91]	0.0046102 [1.06]	0.0012117 [0.82]	0.0011988 [0.71]
Sta.	149.65***	3,945.82***	151.14***	3,910.63***	3,970.10***
N	150	135	150	135	135

Note:
- **, **, and *** means significant level at 10%, 5%, and 1% respectively*
- *FE and RE run all models; then, the Hausman test selects the proper estimation between FE and RE.*
- *The estimation results of FE or RE have heteroskedastic and/or autocorrelation; thus, GLS will fix the model*

There was a positive effect of NIM_{t-1} on NIM in the sample period, but the other independent variables' (SIZE, CAP, LOAN, and DEP) effect on NIM was unclear. In detail, all SIZE coefficients were insignificant; two in five CAP and LOAN coefficients were significantly positive, and three in five DEP coefficients were seriously negative.

Table 6. The effect of fintech on bank performance, control by COVID-19, and bank owner

Variable	Covid-19			Owner		
	ROA	ROE	NIM	ROA	ROE	NIM
PERt-1	0.7449817*** [12.18]	0.7865029*** [14.17]	0.9619687*** [48.89]	0.7280345*** [11.72]	0.7739126*** [13.58]	0.9586257*** [47.82]
SIZE	-0.000144 [-1.25]	-0.002632* [-1.65]	-0.0000622 [-0.97]	-0.0000874 [-0.41]	-0.0016917 [-0.70]	-9.45e-06 [-0.08]
CAP	0.0185103*** [3.68]	-0.002792 [-0.10]	0.0029398 [-0.97]	0.0208889*** [4.06]	0.0080432 [0.28]	0.0037703 [1.24]

LOAN	0.0068157** [2.27]	0.0757112** [2.56]	0.0040062** [2.07]	0.0058869* [1.93]	0.0630197** [2.07]	0.0038873** [1.97]
DEP	-0.0015751 [-0.57]	-0.0107308 [-0.36]	-0.0045135*** [-2.73]	-0.0007873 [-0.28]	0.0015838 [0.05]	-0.0043402** [-2.59]
FIN	0.0004012*** [2.67]	0.0043897** [2.38]	0.0000726 [0.73]	0.000282** [2.13]	0.0028809* [1.73]	4.23e-06 [0.05]
FINt-1	-0.0003627** [-2.18]	-0.0053018** [-2.59]	-0.000038 [-0.35]	-0.0002901* [-1.79]	-0.0042964** [-2.12]	2.79e-07 [0.00]
COV	0.0003299* [1.66]	0.0044952* [1.83]	0.0001735 [1.44]	-	-	-
OWN	-	-	-	-0.0000683 [-0.21]	-0.0012752 [-0.35]	-0.0000798 [-0.40]
Cons	0.002079 [0.74]	0.0668969* [1.78]	0.0011501 [0.69]	0.0013931 [0.30]	0.0546938 [1.05]	0.000406 [0.16]
Sta.	1,091.39***	264.50***	3,992.38***	1,043.77***	245.69***	3,970.51***
N	135	135	135	135	135	135

Note:

- **, **, and *** means significant level at 10%, 5%, and 1% respectively*
- *FE and RE run all models; then, the Hausman test selects the proper estimation between FE and RE.*
- *The estimation results of FE or RE have heteroskedastic and/or autocorrelation; thus, GLS will fix the model.*
- *COV is a dummy variable, COV=1 with covid (from 2020); COV=0 in 2019*
- *OWN is a dummy variable, OWN = 1 State own; OWN = 0 is non-state own*

To discuss the effect of the core variables on bank performance, we found mixed results that were more and less consistent with the existing publications mentioned in the literature review. In detail, the lag of performance variables positively predicted bank performance. For the simultaneous impact of fintech information, the equity to total assets ratio and loan growth increase were positive with ROA, but negative with ROE. Moreover, bank size and deposit change had a negative impact on bank performance. In this study, we explored that despite the significant effect of fintech's development, it was a weak factor compared with the other core variables, especially the lag of the bank performance variables. We considered that the reason could be that the fintech sector was smaller than the banking sector, and it seemed fintech only affected the mobile payment segment (FitchRatings, 2021; Statista, 2021). However, based on fintech's development history, and experience with the effect of fintech on banks globally, we imagined that the role of fintech in the Vietnamese finance market would become more critical than it was at the current time. Furthermore, the estimation result showed that bank performance strongly depended on traditional factors, which might signal a low level of banking transformation.

Robustness check

To check the effect of fintech on bank performance, we considered the factor of bank ownership and COVID-19 in shaping the relationship. First, examining the bank ownership factor was motived by Bonin et al. (2005), Chen and Liu (2013), and Malik et al. (2016). These publications showed that bank ownership was a significant factor in banking performance. Hence, in this study's case, we expected a difference in the influence from the various kinds of bank ownership on bank performance. Based on the collected data, two types of bank ownership were built into a dummy variable called OWN, namely state-owned bank (OWN=1) and non-state-owned bank (OWN =0). Second, motivated by the studies by Demirgüç-Kunt et al. (2021) and Berger and Demirgüç-Kunt (2021) about the influence of COVID-19 on the banking sector, we considered that COVID-19 was a significant factor that might influence bank performance in Vietnam. Based on the outbreak of SAR-CoV-2 at the beginning of 2020 and the collected data, we formulated the dummy variables to express the COVID-19 factor (COV), namely, COV = 0 meant before 2020 and COV = 1 meant since 2020. The estimation results of the influence of OWN and COV on the relationship between fintech and bank performance are given in **Table 6.**

Under the influence of COVID-19 and the kind of bank ownership, the estimation result of the effect of fintech on bank performance was the same as the estimation above **(Tables 3-4-5)**; namely, the fintech variable and the lag of the fintech variable still influenced bank profitability (ROE and ROA) and did not influence NIM. Besides, we explored an exciting finding: The significant impact of the COVID-19 factor on bank profitability. During the COVID-19 pandemic, Vietnamese banks earned higher profits than before. Moreover, different from the findings of Bonin et al. (2005), Chen and Liu (2013), and Malik et al. (2016), there was no evidence to conclude anything about the influence of the bank ownership variable on the relationship between fintech and bank performance.

Conclusion

This paper designed a panel model to investigate the effect of fintech on bank performance based on the existing quantitative studies about the determinant of bank performance. Relying on the information about fintech in Vietnam's top five largest financial websites from January 2019 to June 2021, we apply the Python programming language to collect and anlyze the data. Next, the fintech development variable is calculated by the word frequency statistic, a powerful technique of the text mining approach. Vietstock, a trusted financial statistic organization in Vietnam, provided the dataset to estimate the bank-level variables. The estimation results in this study are the outcomes of the GLS approach, which fixes the heteroscedastic or/and autocorrelation of the FE or RE approach.

As mentioned in Section 4, we find evidence of the significant impact of fintech's development on bank profitability, but it is insensitive on the net interest margin. In detail, fintech's development increases bank profitability, and the lag of fintech's development is a negative factor in bank profitability. Besides, bank performance is generally positively influenced by its lag. Furthermore, there is a consistency in the estimation results between the various models regarding the determinants of bank performance. The ratio of equity to total assets and the growth of loans are positive factors. In contrast, bank size and the growth of deposits are negative factors. Moreover, we explore the exciting finding that there was greater bank profitability during COVID-19 than before.

The findings are significant scientific evidence for the bank and fintech company. This study found a relationship between fintech news in the media and bank performance. Based on that, we suggest that the banks consider establishing a department to collect fintech news; after that, it should be processed and considered as a critical factor in making a strategy to adapt to fintech's development. Besides, the fintech companies might consider cooperating with the media to increase the volume of fintech news, especially about the advantages of fintech products and the benefits when using fintech products in the digital era. It helps to change the mind of consumers to use the financial products of the fintech company. We believe it will be a good tactic for the fintech companies to compete with the traditional commercial banks.

Limitation

The study has some limitations, which are suggestions for further research. First, we used the panel model to estimate the relationship between fintech's development and bank performance. The outcomes are consistent with the positive perspectives about fintech and the banks. However, we argue that the time-series model is a significant way to estimate this relationship. The time-series data of fintech's development should be extended using the text mining approach, and then formulate the bank index for the development. Second, according to Pham et al. (2021), bank fintech indicates the financial institutions' fintech development, including the commercial banks. Besides, a bank's annual report is also unstructured data, which might be used for evaluating fintech's development of the commercial bank with the text mining approach. Therefore, we argue that it might be possible to design the model to investigate the impact of bank fintech on bank performance. The estimation result might provide new knowledge about the link between the banks and fintech. Finally, we consider other techniques of the text mining approach that should be applied for measuring fintech's development variables. It might provide new insight into fintech's development in cyberspace. We argue that it will be a meaningful suggestion for further research.

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