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Impact Of Financial Technology's Growth to Bank's Performance and Efficiency at Pre Pandemic Covid-19

Bella Ananda Chairunnisa
Universitas Muhammadiyah Surakarta, Sukoharjo, Indonesia
Email: bac476@ums.ac.id

Abstract

COVID-19 outbreaks are known as catalysts of digitalization in all industries, including the financial industry, because of the emergence of financial technology. Prior research often illustrated the impact of emerging financial technology on industries at the moment or during a pandemic. However, little attention has been devoted to these impacts during the pandemic. Given a sight from the consumer's perspective, we tried to examine the causality between financial technology's growth and the bank's performance and efficiency. We utilized conventional banks as our population with sample criteria listed banks in Southeast Asia from 2017 to 2019. We employed generalized least squares and the generalized method of moment as regression methods to examine those causalities. Descriptive statistical analysis, determining estimation models, and classical assumption tests were also carried out. A total sample of 102 banks, Our findings suggest that ever since pre-pandemic, financial technology has significantly impacted banks' performance and efficiency. The growth of financial technology caused a significant decrease in the bank's performance and an increase in the bank's efficiency.

Keywords: *Financial Technology, Performance, Efficiency, Banking, Pre-Pandemic*

Abstrak

Wabah Covid-19 diketahui menjadi katalis digitalisasi pada semua industri termasuk industri keuangan melalui munculnya teknologi keuangan. Penelitian sebelumnya sering menjelaskan mengenai dampak teknologi keuangan pada saat atau pasca pandemi. Namun, masih sedikit penelitian yang berfokus pada dampak tersebut sebelum pandemi terjadi. Melihat dari sudut pandang konsumen, peneliti mengkaji hubungan sebab akibat antara pertumbuhan teknologi keuangan terhadap kinerja dan efisiensi bank. Menggunakan populasi bank konvensional dengan kriteria sampel bank yang terdaftar di bursa Asia Tenggara pada tahun 2017 hingga 2019. Peneliti mengoperasikan *Generalized Least Square* dan *Generalized Method of Moment* sebagai metode regresi untuk menguji hubungan tersebut. Selain itu dilakukan juga analisa descriptive statistic, determining estimation model, dan uji asumsi klasik. Dengan total sampel 102 bank, temuan menunjukkan bahwa sejak sebelum pandemi, teknologi keuangan telah berdampak signifikan terhadap kinerja dan efisiensi bank. Pertumbuhan teknologi finansial menyebabkan penurunan kinerja bank secara signifikan dan peningkatan efisiensi bank

Kata kunci: Teknologi Finansial, Kinerja, Effisiensi, Perbankan, Pra Pandemi

1. Introduction

In recent years, the whole world has suffered from the spread of the Covid-19 pandemic. A pandemic caused by a coronavirus which is easily transmitted. The majority of the world's population has been significantly impacted by the pandemic over the years. One of them is that the pandemic forces people to spend more time at home (Beaunoyer et al., 2020). Humans are forced to do everything at home, doing social distancing, and travel only if it is urgent. Over time, this compulsion has an impact on human behavior and habits, including human behavior in carrying out economic activities (Bartik et al., 2020; Chetty et al., 2020; Nicola et al., 2020).The need to stay at home but still obligated to meet life's needs, encourage new behavior such as cashless economic transactions which also directly encourages the acceleration of digital transformation in the financial sector.

The occurrence of the Covid-19 pandemic has indeed encouraged the acceleration of digitalization, but before the outbreak of the Covid-19 pandemic, digitalization had already taken place, including in the financial sector. Digitalization in the financial sector is often known as financial technology (fintech). Unfortunately, the emergence of fintech does not necessarily have a positive impact on all parties. Digitation of physical activity in the form of financial experiences poses challenges for business people in the same industry (Châlons & Dufft, 2017) particularly on the banking sector which the products mostly similar to the product that financial technology enterprise had to accelerate digital transformation (Chishti and Barberis , 2016). Financial technology has a great opportunity to take over some or even all of the functions of traditional banks (Li et al., 2017).

Products offered by financial technology are usually substitutes and disruptive to the old style or long-lasting order or system run by banks. People who prefer and are comfortable with technology, have low trust issues, have good financial literacy have a tendency to use financial technology products compared to banks (Junger & Mietzner, 2020). Based on research, Tiffani (2023) states that people now prefer to use digital banks. In addition, financial technology is also very friendly to people who are not bankable due to insufficient economic capacity, especially in the use of loan services the banks offered (Jagtiani & Lemieux, 2018). Financial Technology is proven to provide alternative financing for business owners who do not have any access to bank loan because of the collateral requirement (Utami, 2023).

A key feature of financial technology is the application of innovative technologies to perform activities that banks normally do such as borrowing, paying, and investing (Brandl & Hornuf, 2020; Puschmann, 2017; Chisti & Barberis, 2016). Fintech develops practical applications to increase efficiency in financial services, such as contactless and instant payments, asset management services, investment advice and financial services. The presence of financial technology can be said to be a new player in the financial industry which is directly a competitor to banks because they have products that are similar to other. On the other hand, the development of financial technology has also led to bank efficiency. The competitive efficiency hypothesis states that competition causes banks to specialize in certain types of debt to specific borrowers and makes managers adapt to technological developments, thereby reducing customer lending procedures and monitoring costs (Tan & Floros, 2018).

The presence of financial technology has a direct impact on the banking industry. The increase in the number of users and total transactions using fintech, as well as the growth in the number of fintech companies are known to significantly reduce the performance of the banking industry (Phan et al., 2020). Fintech is able to reduce information asymmetry through high transparency which will increase consumer trust in the platforms they use and encourage consumers to switch to fintech and leave banks (Junger & Mietzner, 2020). On the other side, there is only few prior research that examining the impact of fintech on bank efficiency. Even though according to research, the presence of fintech actually makes banks more efficient, which will lead a positive effect on their performance (Onorato et al., 2023). In this study, we found that the growth of financial technology give significant impact to bank’s performance and efficiency. Even though according to research, the presence of fintech actually makes banks more efficient, which will lead a positive effect on their performance (Onorato et al., 2023). Conceptually, this phenomenon can be explained by two theories, namely consumer theory which briefly states that new services that meet consumer demands or desires can replace old types of services (Levin & Milgrom, 2004). Another theory is disruptive innovation theory which briefly states that new players who provide innovative technology that is more easily accessible and more cost effective can create new competition in the market, and over time will be able to replace or disrupt the system or order that already existed before (King and Baatartogtokh, 2015) .

FinTech in Indonesia has developed very rapidly from year to year. The World Bank released data on FinTech users, only 7% in 2007 had grown to 20% in 2011, rose again to 36% in 2014, and 2017 increased by 78%, with the total value of FinTech transactions in Indonesia in 2017 estimated to reach IDR 202.77 Trillion (OJK, 2023a). Meanwhile, according to OJK data in November 2022, banking performance in Indonesia is relatively stable and robust, as can be seen from banking credit growth of 11.16 per cent, while the collection of Third Party Funds (DPK) grew by 8.78 per cent from the previous year. Banking risk indicators are also maintained, as reflected in the AL/NCD and AL/DPK ratios of 134.97 per cent and 30.42 per cent, respectively. This liquidity ratio is still far above the threshold but lower than the previous year due to accelerated credit distribution and policies. Increase in GWM ratio. Bank capital is also relatively strong with a CAR of 25.49 per cent, and credit risk tends to decrease where the gross NPL and net NPL ratios are 2.65 per cent and 0.75 per cent, respectively, while Loan at Risk is 15.12 per cent (OJK, 2023b).

This research is aimed to examining and analyzing the impact of financial technology growth to bank's performance and efficiency. While prior study mentioned that there is positive significant effect in the relationship between financial technology growth and bank's performance and efficiency (Phan et al., 2020). In line with prior research, we also found that the growth of financial technology give significant impact to bank's performance and efficiency.

2. Literature Review

2.1 Consumer Theory

The impact of financial technology's existence on bank performance can be explained by using the Consumer Theory. Consumer theory focuses on how a rational consumer will make consumption decisions. When consumers make decisions, there are several factors that influence them. one of which is the accelerated growth of digital innovations such as artificial intelligence , virtual reality, blockchain, and automated shopping system (Lee & Lee, 2020). This technology allows consumers to obtain better service and generates value propositions (Zaki, 2019). Consumer theory often uses utility functions to represent individual preferences. Consumer theory also states that new services that meet consumer demand are considered more capable of increasing utility, consumers can replace old types of services (Aaker et al., 1990).

2.2 Disruptive Theory

The theory of innovation disruption explains how a system, an order, or a business player can be replaced by the emergence of new players who offer a system, a new order which is then better able to adapt to the needs of consumers at that time (King and Baatartogtokh, 2015). Some of the statements mentioned in this theory are: The pace of continuous innovation targets consumer needs, which then opens up opportunities for disruptive innovators; Existing players have the capability to respond but often fail to take advantage of the situation; The fear/defeat of existing players is the result of a disruption. The theory of innovation disruption also states that new players who provide innovative technology to make it more accessible and more cost effective can create new competition in the market (Christensen, 1997).

2.3 Financial Technology

The emergence of Fintech is inseparable from the world financial crisis in 2008. Public distrust of banks at that time provided a new opening for innovation in finance. In addition, the emergence of Fintech is certainly inseparable from the progress and rapidity of technological developments that occur, including the acceleration of computational power, data creation, and fast connectivity. Financial Technology or often shortened to fintech is a fairly new alternative in conducting financial activities. Fintech includes a new wave that is changing the way people pay, send money, borrow, lend and invest (Chishti and Barberis, 2016). Fintech is predicted to be a revolution that reshapes the financial ecosystem, creating a competition that gives birth to new winners and losers. Fintech is considered as an entrant that challenges incumbents (companies that have existed before) to include various players changing the way back office, middle office, and financial system regulation (Arslanian et al., 2019).

2.4 Bank Performance

Banking performance has a broad definition and it is generally quite difficult to measure a bank's performance by one specific measure. Bank performance can be measured through many indicators, according to Kedia (2016), one of which is bank profitability. Profitability can be used as a benchmark to measure performance by using profitability ratios as a proxy such as the ratio of total loans to total assets, return on asset ratio, return on equity ratio, net interest margin, etc. Banks that have a high profitability ratio are considered to have good performance. According to Nouaili, Abaoub, & Ochi (2015) Bank performance is positively associated with capitalization, privatization and quotation. Meanwhile, according to Khalfaoui & Saada, (2015) Credit risk, liquidity, total assets and disclosure of information relating to credit are the primary determinants of bank performance. However, in this research, based on research conducted by Phan et al (2020), bank performance is predicted through several indicators, namely Return on Assets, Return on Equity, Net Interest Margin, and Tobbins'Q value.

2.5 Bank Efficiency

There are different views regarding the relationship between competition and efficiency in banking, between the competition-inefficiency hypothesis and the competition-efficiency hypothesis. Competition-inefficiency hypothesis states that competition will reduce efficiency in banking, for example in research Tan & Floros (2018) stated that the higher the competition in banks, the greater the tendency of customers to switch to other service providers, which then increases information asymmetry and banks have to increase their allocation. other resources for screening and monitoring borrowers. Meanwhile, the competition-efficiency hypothesis states the opposite, namely that increasing competition causes banks to specialize certain types of debt to certain borrowers and makes managers try to adapt with technological developments so that it can reduce costs in lending procedures by customers and monitoring costs (Tan & Floros, 2018).

2.6 Financial Technology and Bank Performance

Prior researches stated that the growth of financial technology companies has a negative impact on bank performance, which is judged by the decline in bank profitability. The decline in the number of transactions in the banking industry shows that the presence and growth of financial technology companies has made consumers/customers more or less now switch from banking products to financial technology products (Phan et al 2019). In addition, it was also found that financial technology companies reach a larger scale than banks. People who cannot go to the bank because of their economic inadequacy (regarding borrowing) then turn to financial technology company products as a solution for them to get loans (Jagtiani and Lemineux 2018). Of course, this makes the number of transactions of financial technology companies increase. Coupled with their convenience, financial technology companies are perfect competitors offered for core bank products such as payments, loans, transfers. From the explanation above, the author drew a hypothesis that **Hypothesis one is Financial technology growth has a negative effect on bank performance**.

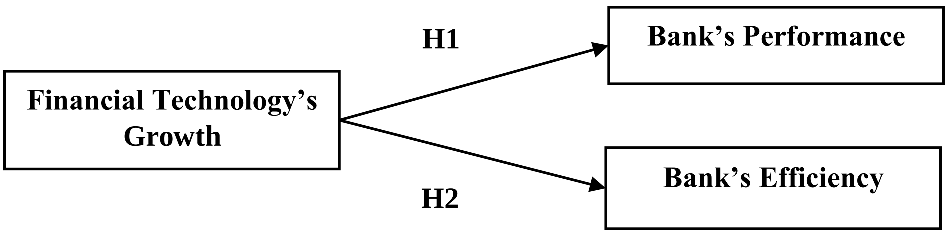
2.7. Financial Technology and Bank Efficiency

The presence of financial technology as a competitor to banks is considered to make competition in the financial industry, especially banking with financial technology, increasingly tight. In accordance with the competition-efficiency hypothesis, higher competition makes banks act more efficiently and causes banks to specialize certain types of debt to certain borrowers and makes managers try to adapt to technological developments so as to reduce costs in borrowing procedures by customers and monitoring costs (Tan and Floros 2018). Therefore, the author drew the second hypothesis, **second hypothesis is Financial Technology Growth Has a Positive Effect on Bank Efficiency.**

2.8 Research Framework

The research framework is drawn as follows:

Image 1. Research Framework



Source : Researcher, 2023

3. Research Method

3.1 Research Design

This is an explanatory research with a quantitative approach. This study examines how the influence of financial technology's growth on bank performance and efficiency. The population of this study was conducted at several commercial banks in ASEAN-6, those are in Indonesia, Malaysia, Singapore, Thailand, the Philippines, and Vietnam that met the sample criteria, during the two years of the study, namely 2017-2019. The data used in this study is secondary data (archival data) in the form of bank's financial statements and several studies on the development of financial technology in ASEAN. The research sample was obtained using a purposive sampling technique. Finally, there were 102 banks in six countries with 306 observations.

3.2 Operational Variables

The variables operated in this study include the dependent variable, namely performance measured by Return on Asset (ROA), Return on Equity (ROE), Net Interest Margin (NIM), and Tobbin's Q (Phan et al., 2020) while bank efficiency as measured by Data Envelopment Analysis (DEA) (Tan and Anchor, 2017) and Operating Efficiency Ratio (OER). The independent variable is Fintech growth measured by its transaction magnitude, number of Fintech users, number of Fintech companies in annual. Control variables are bank size, bank capital ratio, loan loss provision, gross domestic product, inflation rate and country in each country (Phan et al., 2020).

3.3 Data Analysis

This study uses panel data with abnormal data distribution. Testing carried out in this research referring to Phan et al., 2020 are:

a) **Descriptive Statistic**. Describes the data used in research. Descriptive statistics in this research include mean, median, standard deviation, minimum value and maximum value of all variables implemented in the research.
b) **Determining Estimation Model**. Chow, Hausman, and Lagrange Multiplier tests are carried out to determine which model can be operationalized (Common, Fixed, or Random Effect) before hypothesis testing is carried out.
c) **Classic Assumption Test.** Classical Assumption Testing is carried out to fulfill the requirements for carrying out multiple regression testing. The classic assumption test consists of linearity, normality, heteroscedasticity, multicollinearity and autocorrelation tests.

d) **Hypothesis Testing**. Hypothesis testing in this research was carried out using the t-test, namely to find out how much influence the independent variable has on the dependent variable. Also the probability value (p-value) of the independent coefficient. If the p-value is below the significance percentage, namely 10%, then the hypothesis is accepted. Meanwhile, the significance percentages are 10% (0.1), 5% (0.05), and 1% (0.01). Apart from that, a coefficient of determination or R^2 test was carried out to find out how strongly the independent variable influences the dependent variable for each variable. Finally, an F test is carried out, to find out how the independent variables together have an influence on the dependent variable

3.4 Generalized Least Square Models

This study uses panel data with unnormal data distribution. Testing carried out in this research are descriptive statistic analysis, determination of best model, and hypothesis testing. All data testing and analysis processed by EViews9 with the Generalized Least Square testing technique for the main regression and the Generalized Method of Moments for Robustness Check. Referring to Phan et al., 2020, the models in this study are:

PERFi,t = α + β 1FINTECHi,t + β 2CAPi,t + β 3SIZEi,t + β 4LLPi,t + β 5GDPi,t + β 6INFi,t + β 7COUNTRYi,t + ε i, t…. (1)

EFFi,t = α + β 1FINTECHi,t + β 2CAPi,t + β 3SIZEi,t + β 4LLPi,t + β 5GDPi,t + β 6INFi,t + β 7COUNTRYi,t + ε i, t…. (2)

Meanwhile for robustness test, the formula we operated are:
PERFi,t = α + β 1FINTECHi, t-1 + β 2 KINERJAi, t-1 + β 3CAPi,t-1 + β 4SIZEi,t-1 + β 5LLPi,t-1 + β 6GDPi,t-1 + β 7INFi,t-1 + β 8COUNTRYi,t-1 + ε i, t- 1… (3)

EFFi,t = α + β 1FINTECHi, t-1 + β 2 EFISIENSIi, t-1 + β 3CAPi,t-1 + β 4SIZEi,t-1 + β 5LLPi,t-1 + β 6GDPi,t-1 + β 7INFi,t-1 + β 8COUNTRYi,t-1 + ε i, t- 1… (4)

4. Result and Discussion
4.1 Descriptive Statistic

It should be noted this research has unnormal data distribution, so the descriptive statistic as followed:

Table 1. Descriptive statistic

	Observation	Minimum	Maximum	Deviation Std
Transaction	306	5,928	39,356	11,131
User	306	2.150	121.2	38.59
Enterprise	306	94.00	1170	221.6
Return on Asset	306	-0.122	0.102	0.017
Return on Equity	306	-1.325	0.348	0.121
Net Interest Margin	306	0.004	0.225	0.044
Tobbin’s Q	306	0.784	3.286	0.238
Data Envelopment Analysis	306	0.496	0.972	0.052
Operational Efficiency Ratio	306	0.133	5.548	0.982
Capital	306	0.032	0.992	0.084
Size	306	8.998	15.17	1.352
Loan Loss Provision	306	0.003	0.232	0.030
Gross Domestic Product	306	0.007	0.071	0.012
Inflation	306	0.003	0.059	0.013

Source: secondary data processed, 2023

4.2 Determining Estimation Model

To get the best estimation model, this research operates several tests, those are Chow Test; Hausman Test; and Lagrange Multiplier Test. All of testing are proceed by Eviews 9 software.
Chow test is used to determine which better between Common Effect Model (CEM) and Random Effect Model (REM).

Table 2. Chow test

Redundant Fixed Effects Tests			
Equation: FEM_TOBBINSQ			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	4,047914	-101.196	0
Cross-section Chi-square	344,8155	101	0
Redundant Fixed Effects Tests			
Equation: FEM_DEA			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	3,738831	-101.196	0
Cross-section Chi-square	328,5999	101	0

Source: secondary data processed, 2023

Based on the results of the Show test above to determine the CEM or FEM estimation model, it was found that both models have a probability of 0.000. Therefore, while the FEM is selected and the test is continued to the Hausman Test to find out the best FEM or REM estimation model to operate. Hausman test is used to determine which better between Fixed Effect Model (FEM) and Random Effect Model (REM).

Table 3. Hausman test

Correlated Random Effects - Hausman Test			
Equation: REM_DEA			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	14,130775	8	0,0784
Correlated Random Effects - Hausman Test			
Equation: REM_TOBBINSQ			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	5,518240	8	0,7010

Source: secondary data processed, 2023

Based on the table 3., it is known that the probability value of Chi square is more than 0.05. This means that the REM estimation model is better than FEM. Therefore, the test is continued with the Lagrange Multiplier Test to find out the best estimation method is REM or CEM. Lagrange Multiplier test is used to determine which better between Common Effect Model (CEM) and Random Effect Model (REM).

Table 4. Lagrange multiplier test

Lagrange Multiplier Tests for Random Effects (DEA)
Null hypotheses: No effects

Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives			
	Cross-section	Test Hypothesis Time	Both
Breusch-Pagan	62,13265	0,470615	62,60327
	(0,0000)	(0,4927)	(0,0000)
Lagrange Multiplier Tests for Random Effects (TOBBINSQ)			
Null hypotheses: No effects			
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives			
	Cross-section	Test Hypothesis Time	Both
Breusch-Pagan	62,13265	0,470615	62,60327
	(0,0000)	(0,4927)	(0,0000)

Source: secondary data processed, 2023

Based on the results of the Lagrange Multiplier test above, it is found that the probability of Both Breusch Pagan is less than 0.05, which is 0.000. Therefore, the best estimation method for this research is REM (Random Effect Model).

4.3 Hypothesis testing

Continued to hypothesis testing, in this study used the Generalized Least Square (GLS) method to be operated in regression process because based on previous testing, the Random effect Model (REM) was chosen as the best effect for hypothesis testing. From the results of hypothesis testing, t-test, and F-test, it can be seen how the influence of the independent variable is to the dependent and how strong the influence.

a. **Hypothesis 1. :** The growth of financial technology has a negative effect on bank performance.
The first hypothesis in this research is "the growth of financial technology has a negative effect on bank performance". In this research, financial technology (Fintech) is represented as a proxy for the number of annual transactions (Transaction), the number of annual Fintech users (User), and the number fintech companies that operate every year (Enterprise). Bank performance is represented in four proxies, namely ROA, ROE, NIM, and Tobbin's Q. Based on each proxy operated in the research for hypothesis one, there is only one of the results that is not significant, namely the influence of annual transactions on the amount of NIM value.

The majority of results from the regression for the first hypothesis are significantly positive (namely the effect of Transaction to ROA, ROE; User Tobbins Q; Enterprise on ROA, ROE, and NIM) and the rest have a significant negative effect (Transaction on Tobbins Q; User on ROA, ROE, NIM; Enterprise on Tobbins Q), from the results which have a significant negative effect meaning that it is true that the higher the value, the lower the bank's performance. So, the higher the number of annual transactions with fintech, the lower the bank's Tobbins Q value. The higher the number of annual users of a fintech, the lower the ROA; ROE; and bank NIM. The more fintech companies operate, the lower the bank's Tobbins Q. On the other hand, the higher the number of annual transactions with fintech, the higher the bank's ROA and ROE. The higher the number of annual fintech users, the higher the bank's Tobbins Q. Lastly, the more fintech companies operate, the higher the ROA; ROE; and bank NIM.

b. **Hypothesis 2. : T**he growth of financial technology has a positive effect on bank efficiency.
In this research, financial technology (Fintech) is represented as a proxy for the number of annual transactions (Transaction), the number of annual Fintech users (User), and the number of fintech

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companies operating each year (Enterprise). Bank efficiency is represented in two proxies, namely Data Envelopment Analysis (DEA) and Operating Efficiency Ratio (OER).

Considering to each proxy operated in the research for hypothesis two, there was only one of the six results that was not significant (look forward to table 5), namely the influence of the number of fintech companies operating on the DEA value. The majority of the results from the regression for the second hypothesis are significantly negative (namely the influence of Transaction on DEA and OER; Enterprise on DEA and OER), and the remainder (the influence of Users on OER) is significantly positive. So, the higher the number of annual transactions with fintech, the lower the efficiency (DEA and OER) of the bank. Also the higher the number of fintech companies operating, the higher the efficiency (OER) of the bank. On the other hand, the higher the annual fintech users, the higher the efficiency (DEA and OER) of the bank.

4.4 Control Variables

The control variables in this research are Size, Capital, LLP, GDP, and INF, as well as the country dummy. The variable Size or bank size has a significant positive effect on ROE. NIM, and OER. Size has a significant negative effect on DEA, an insignificant positive effect on Tobbin’s Q, and an insignificant negative effect on ROA. The Capital variable or bank capital ratio has a significant positive effect on ROE and Tobbin’s Q. Capital has a significant negative effect on DEA, an insignificant positive effect on OER, and an insignificant negative effect on ROA and NIM. The LLP (Loan Loss Provision) variable has a significant positive influence on Tobbin’s Q, DEA and OER. LLP has a significant negative effect on ROA, ROE and NIM. The GDP (Gross Domestic Product) variable has a significant positive influence on ROA, ROE, NIM, and Tobbins Q. Meanwhile, on DEA and OER, GDP has a significant negative influence. The INF variable (inflation) has a significant positive effect on OER, a significant negative effect on NIM, Tobbin’s Q, and DEA. It has an insignificant positive effect on ROE, and an insignificant negative effect on ROA.

Table 5. hypothesis test, t-test, and f-test result by GLS method

	Performance				Efficiency	
	ROA	ROE	NIM	Tobbin’s Q	DEA	OER
Transaction	3.28E-07	2.11E-06	1.49E-09	-3.33E-06	-2.92E-06	-9.52E-06
	(0.0000)***	(0.0000)***	-0.9795	(0.0000)***	(0.0000)***	(0.0024)***
User	-0.0002	-0.0008	-0.0002	0.0013	0.0014	0.0073
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Enterprise	3.94E-06	2.87E-05	8.46E-06	-0.0002	-1.40E-05	-0.0008
	(0.0028)***	(0.0100)***	(0.0018)***	(0.0021)***	-0.108	(0.0000)***
Size	-0.0014	0.0148	0.0088	0.0174	-0.0498	0.5443
	-0.3416	(0.0919)*	(0.0111)**	-0.5898	(0.0000)***	(0.0000)***
Capital	-0.0007	0.0632	-0.0087	0.5498	-0.0524	0.0761
	-0.4413	(0.0864)*	-0.2752	(0.0000)***	(0.0003)***	-0.7559
LLP	-0.184	-0.7342	-0.0235	0.8457	0.33	9.7644
	(0.0000)***	(0.0000)***	(0.0034)***	(0.0046)***	(0.0000)***	(0.0000)***
GDP	0.0538	0.5877	0.107	0.6089	-0.6177	-4.818
	(0.0018)***	(0.0000)***	(0.0001)***	(0.0209)**	(0.0000)***	(0.0001)***
INF	-0.0057	0.0343	-0.0258	-0.4694	-0.1676	1.4752
	-0.4989	-0.5029	(0.0168)**	(0.0000)***	(0.0000)***	(0.0062)***
Constant	0.0256	-0.1549	-0.0635	0.7764	1.4938	-5.723
	-0.1525	-0.1848	-0.1519	(0.0717)*	(0.0000)***	(0.0000)***
Dummy	Yes	Yes	Yes	yes	Yes	Yes
F-stats	265.35	237.68	312.97	47.62	245.82	678.64
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
AR2	0.989	0.988	0.991	0.943	0.988	0.996

	Performance				Efficiency	
	ROA	ROE	NIM	Tobbin's Q	DEA	OER
Observation	306	306	306	306	306	306

Source: secondary data processed, 2023

The table above is the regression result of performance model measured with ROA, ROE, NIM, Tobbins Q, and efficiency model as measured by the DEA and OER proxies. Both models were regressed using the GLS estimation method. F-stats correspond to p-values, while *, **, and *** refer to the 10%, 5% and 1% significance levels.

4.5 Robustness Check by GMM

The use of Generalized Method of Moment (GMM) means that a distributed lag effect variable is included in the model, this is to test whether the value of the variable in year t-1 has an influence on the value of the variable in year t. Based on table 3 and table 4 which have been written below, it can be seen that the robustness check results in the performance model (look forward to table 6) giving result there is no independent variable proxy that has a significant effect on the dependent variable proxy. Likewise, the results of the robustness check in the efficiency model (look forward to table 7), there is no independent variable proxy that has a significant effect on the dependent variable proxy. However, the regression results in the two models have the same direction as the regression results using GLS.

Table 6. robustness check on performance model

	Performance			
	ROA	ROE	NIM	Tobbins's Q
Performance(-1)	0.0669 (0.9677)	0.1158 (0.9053)	-5.5395 (0.9815)	20.87 (0.9744)
Transaction(-1)	4.49E-05 (0.8846)	0.0005 (0.8159)	0.0002 (0.9829)	-0.0001 (0.9518)
User(-1)	-0.0152 (0.8839)	-0.1691 (0.8155)	-0.0690 (0.9828)	0.0501 (0.9658)
Enterprise(-1)	0.0002 (0.8803)	0.0023 (0.8175)	0.0012 (0.9826)	-0.002 (0.9715)
Size (-1)	-0.1705 (0.8996)	-2.2491 (0.8252)	-0.1766 (0.9875)	13.581 (0.9771)
Capital(-1)	-1.1904 (0.8859)	-13.378 (0.8183)	-5.4004 (0.9830)	-3.2328 (0.9534)
LLP(-1)	0.7445 (0.9078)	9.3548 (0.8379)	4.5658 (0.9824)	0.7027 (0.9852)
GDP(-1)	4.4892 (0.8828)	49.89 (0.8151)	21.66 (0.9828)	8.4754 (0.9570)
INF(-1)	10.1440 (0.8857)	114.46 (0.8169)	46.294 (0.9829)	8.1563 (0.9750)
Dummy	Yes	Yes	Yes	Yes
Observations	204	204	204	204

Source: secondary data processed, 2023

The table above is the regression result from performance model as measured by the ROA, ROE, NIM, Tobbins Q proxies, the model is regressed using the GMM estimation method using the PERFORMANCE (-1) dependent variable proxy and adjusted for the dependent variable being operated. For example, what is being operated is ROA, then the PERFORMANCE variable (-1) refers to ROA (-1), and so on. The *, **, and *** signs refer to the 10%, 5% and 1% significance levels.

Table 7. Robustness check on efficiency model

	Efficiency Model	
	DEA	OER
EFFICIENCY(-1)	0.3311 (0.8957)	-0.6222 (0.6051)
Transaction(-1)	-3.95E-05 (0.5844)	0.0023 (0.8190)
User(-1)	0.0127 (0.6035)	-0.7762 (0.8200)
Enterprise(-1)	-0.0004 (0.4346)	0.0124 (0.7907)
Size(-1)	-0.2617 (0.5878)	-10.801 (0.8391)
Capital(-1)	-1.1146 (0.6403)	-62.851 (0.8247)
LLP(-1)	1.0763 (0.5950)	55.7678 (0.8010)
GDP(-1)	4.3008 (0.5491)	236.46 (0.8131)
INF(-1)	9.5693 (0.5583)	537.98 (0.8179)
Dummy	Yes	Yes
Observations	204	204

Source: secondary data processed, 2023

The table above is the regression result from efficiency model, as measured by the DEA and OER proxies, the model is regressed using the GMM estimation method using the proxy variable EFFICIENCY (-1) dependent and adjusted for the dependent variable being operated. For example, if the operation is DEA, then the EFFICIENCY variable (-1) refers to DEA (-1), and if the operation is the OER proxy, then the EFFICIENCY variable (-1) refers to OER(-1). The *, **, and *** signs refer to the 10%, 5% and 1% significance levels

4.6 Discussion

Financial Technology Growth has negative effect on Bank Performance

Based on the results of the tests that have been carried out, it was found that the majority of proxies for the fintech variable had a significant negative effect on the majority of bank performance proxies. This is in line with previous research conducted by Phan et al. (2020).This means that the higher the fintech growth, the lower the bank's performance will be. The majority of the results of the regression for the first hypothesis are positive and significant (that is, on the effect of Transaction on ROA, ROE, NIM; User on Tobbin'sQ; Enterprise on ROA, ROE, NIM) and the rest have a significant negative effect (Transaction on Tobbins Q; User on ROA, ROE , NIM; Enterprise to Tobbin'sQ), from the results that have a significant negative effect, it means that the higher the value, the lower the bank's performance. So, the higher the number of annual transactions with fintech, the lower the ROA, ROE, and NIM of the bank. The higher the number of annual fintech users, the lower the bank's Tobbin's Q. The more fintech companies operate, the lower the bank's ROA, ROE, NIM. On the other hand, the higher the number of annual transactions with fintech, the higher the bank's Tobbin'sQ. The higher the number of annual fintech users, the higher the ROA, ROE, NIM of the bank. Lastly, the more fintech companies operate, the higher the bank's Tobbin'sQ.

Financial Technology Growth Has a Positive Effect on Bank Efficiency

Based on the results of the tests that have been carried out, it was found that the majority of proxies for the fintech variable had a significant positive effect on the majority of bank efficiency proxies.

This is in line with previous research conducted by Tan and Floros (2018). Based on each of the proxies operated in the study for hypothesis two, there is only one of the six results that are not significant, namely the effect of the number of fintech companies operating on the DEA value. The majority of the results of the regression for the second hypothesis are positively significant (ie on the effect of Transaction on DEA and OER; User on DEA and OER; Enterprise on DEA), and the rest (effect of Enterprise on OER) is negative significant. Hence, the higher the number of annual fintech users, the higher the efficiency (DEA and OER proxies) of the bank. On the other hand, the higher the annual transaction with fintech, the more fintech companies operate, the lower the efficiency (DEA and OER proxies) of the bank.

5. Conclusion

This study examines the effect of the growth of financial technology on bank performance and efficiency. This research was conducted in a three-year research period, from 2017 to 2019 with the research sample being commercial banks operating in six Southeast Asian countries, namely Indonesia, Malaysia, Singapore, Thailand, the Philippines, and Vietnam. The sample banks must have been listed on the nearby Stock Exchange at least during the study period. The operating variables in this study are Performance (ROA, ROE, NIM, and TobbinsQ) and Efficiency (DEA and OER) as the dependent variable, Fintech (number of annual transactions, number of annual users, number of companies operating annually) as the independent variable. Control variables namely Size, Capital, LLP, GDP, INF, and Country dummy.

Based on the results of the regression carried out using the Generalized Least Square estimation method and robustness check with the estimation method Generalized Method of Moment, gives the result that the two hypotheses proposed are both accepted. So it can be concluded that it is true that the growth of financial technology has a negative effect on bank performance. The higher the growth of financial technology, the lower the impact of bank performance (on several measures of bank performance operated in this study). In addition, for the second hypothesis it is true that the higher the growth of financial technology, the more efficient the bank (on several criteria of banks operated in this study). Researchers in conducting this research, of course there are shortcomings and limitations. The limitations of this study are the limited data collection and the less long research period, so that it certainly affects the strength of the research results. This limitation can be used as a recommendation and corrected by future researchers who research similar things to this study

6. References

Aaker, D. A., Lane Keller, K., Chakravarti, D., Farquhar, P., Reibstein, D., Simon-son, ltamar, Shocker, A., & Stayman, D. (1990). Consumer Evaluations of Brand Extensions. In *Journal of Marketing* (Vol. 54).

Arslanian, Henri and Fabrice Fischer (2019). The Future o Finance: The Impact of Fintech, AI, and Crypto in Financial Services. London: Palgrave Macmillan

Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). *Nber Working Paper Series How Are Small Businesses Adjusting To Covid-19? Early Evidence From A Survey*. http://www.nber.org/papers/w26989

Beaunoyer, E., Dupéré, S., & Guitton, M. J. (2020). COVID-19 and digital inequalities: Reciprocal impacts and mitigation strategies. *Computers in Human Behavior*, *111*. https://doi.org/10.1016/j.chb.2020.106424

Brandl, B., & Hornuf, L. (2020). Where Did FinTechs Come From, and Where Do They Go? The Transformation of the Financial Industry in Germany After Digitalization. *Frontiers in Artificial Intelligence*, *3*. https://doi.org/10.3389/frai.2020.00008

Châlons, C., & Dufft, N. (2017). The Role of IT as an Enabler of Digital Transformation. In *Management for Professionals: Vol. Part F590* (pp. 13–22). Springer Nature. https://doi.org/10.1007/978-3-319-31824-0_2

Chetty John Friedman Nathaniel Hendren Michael Stepner, R. N., Chodorow-Reich, G., Furman, J., Jaravel, X., Katz, L., Saez, E., Straub, L., Yagan, D., Bell, M., Bruich, G., Chelidze, T., Chu, L., Cineus, W., Devlin-Foltz, S., Droste, M., Felton Spence, S., Gaur, D., Gonzalez, F., Gray, R., … Zhang, R. (2020). *Nber Working Paper Series How Did Covid-19 And Stabilization Policies Affect Spending And Employment? A New Real-Time Economic Tracker Based On Private Sector Data*. www.tracktherecovery.org

Chishti, S., & Barberis, J. (2016). The Fintech book: The financial technology handbook for investors, entrepreneurs and visionaries. John Wiley & Sons.

Christensen, C. M. (1997). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Harvard Business School Press. Boston . Massachusetts.

Jagtiani, J., & Lemieux, C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business*, *100*, 43–54. https://doi.org/10.1016/j.jeconbus.2018.03.001

Jünger, M., & Mietzner, M. (2020). Banking goes digital: The adoption of FinTech services by German households. *Finance Research Letters*, *34*. https://doi.org/10.1016/j.frl.2019.08.008

Hamdi, K., & Saada, M. B. (2015). The determinants of banking performance: Empirical evidence from Tunisian Listed Banks. *International Journal of Finance & Banking Studies* (2147-4486), 4(2), 21-28.

Kedia, N. (2016). Determinants of profitability of Indian public sector banks. *Ira-International Journal of Management & Social Sciences*, 2(3), 1-16. https:// doi.org/10.21013/jmss.v2.n3.p1

King, A. A., & Baatartogtokh, B. (2015). How useful is the theory of disruptive innovation?. *MIT Sloan management review*, 57(1), 77.. https://www.researchgate.net/publication/283877064

Lee, S. M., & Lee, D. H. (2020). "Untact": a new customer service strategy in the digital age. In *Service Business* (Vol. 14, Issue 1). *Springer*. https://doi.org/10.1007/s11628-019-00408-2

Levin, J., & Milgrom, P. (2004). Consumer theory. Available from internet: http://web. stanford. edu/~ jdlevin/Econ, 20202.

Li, Y., Spigt, R., & Swinkels, L. (2017). The impact of FinTech start-ups on incumbent retail banks' share prices. *Financial Innovation*, *3*(1). https://doi.org/10.1186/s40854-017-0076-7

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., & Agha, R. (2020). The socio-economic implications of the coronavirus pandemic (COVID-19): A review. In *International Journal of Surgery* (Vol. 78, pp. 185–193). Elsevier Ltd. https://doi.org/10.1016/j.ijsu.2020.04.018

Nouaili, M., Abaoub, E., & Ochi, A. (2015). The determinants of banking performance in front of financial changes: Case of trade banks in Tunisia. *International Journal of Economics and Financial Issues*, 5(2), 410– 417. Retrieved from https://doi.org/21464138

Onorato, G., Pampurini, F., & Quaranta, A. G. (2023). Lending Activity Efficiency. A Comparison Between Fintech Firms And The Banking Sector. *Research in International Business and Finance*, 102185. https://doi.org/10.1016/j.ribaf.2023.102185

OJK, 2023a. Sadari, Amati, Ikuti Perkembangan Financial Technology, https://sikapiuangmu.ojk.go.id/FrontEnd/CMS/Article/10424.

OJK, 2023b. Siaran Pers : Kinerja Perbankan Yang Kuat Dan Stabil Dorong Optimisme Di Tengah Gejolak Global, https://ojk.go.id/id/berita-dan-kegiatan/siaran-pers/Pages/Kinerja-Perbankan-yang-Kuat-dan-Stabil-Dorong-Optimisme-di-Tengah-Gejolak-Global.aspx

Phan, D. H. B., Narayan, P. K., Rahman, R. E., & Hutabarat, A. R. (2020). Do financial technology firms influence bank performance? *Pacific Basin Finance Journal*, *62*. https://doi.org/10.1016/j.pacfin.2019.101210

Puschmann, T. (2017). Fintech. *Business and Information Systems Engineering*, *59*(1), 69–76. https://doi.org/10.1007/s12599-017-0464-6

Tan, Y., & Anchor, J. (2017). The impacts of risk-taking behaviour and competition on technical efficiency: Evidence from the Chinese banking industry. *Research in International Business and Finance*, *41*, 90–104. https://doi.org/10.1016/j.ribaf.2017.04.026

Tan, Y., & Floros, C. (2018). Risk, competition and efficiency in banking: Evidence from China. *Global Finance Journal*, *35*, 223–236. https://doi.org/10.1016/j.gfj.2017.12.001

Tiffani, I. (2023). Pengaruh Literasi Keuangan Dan Literasi Digital Terhadap Preferensi Bank Digital. MBIA, 22(1), 152–167. https://doi.org/10.33557/mbia.v22i1.2039

Utami, N. (2023). Analysis of the Use of Financial Technology and Financial Literacy Among MSMEs. MBIA, 22(1), 11–21. https://doi.org/10.33557/mbia.v22i1.2217.

Zaki, M. (2019). Digital transformation: harnessing digital technologies for the next generation of services. *Journal of Services Marketing*, *33*(4), 429–435. https://doi.org/10.1108/JSM-01-2019-0034

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