Analyzing the Impact of Digital Payment on Efficiency and Productivity of Commercial Banks – A Case Study in China

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Abstract

Digital payment has become one of the most popular payment methods all around the world, especially in countries that witnessed the rapid development of internet. As a traditional financial institution, commercial banks have been impacted by newly developed payment technology since third payment platforms have attracted customers to use the digital payment for daily consumption, transferring, and even investment. This paper focuses on analyzing whether and how the commercial banks in China have been affected by digital payment by using empirical methods. Systematic Generalized Method of Moments (SYS-GMM) is used to test the relationship between the productivity of commercial banks and digital payment. Panel Vector Auto-Regression (Panel VAR) is then applied to evaluate the long-term impact of the growth in digital payment on the efficiency of commercial banks, which is calculated by the Malmquist Productivity Index (MPI). The result based on data from 81 banks in China between 2013-2019 suggests that bank-involved digital payment is beneficial to both profitability and productivity of commercial banks, and third-party digital payment harms the profitability but is not a granger cause of productivity.

Keywords
Digital payment, commercial banks, profitability of commercial banks

1. Introduction
Digital payment, also known as electronic payment, refers to the payment method that does not involve physical cash and uses digital currency, which enables the payers and payees to send receive money online. With the development of the internet and the popularity of mobile phones, digital payment has been widely adopted for commercial transactions (Oney et al. 2017). To provide better service and develop digital payment systems (DPSs), more countries allow diverse digital payment platforms to be established (Yu et al. 2002). As one of the largest countries in the world, China has started a payment revolution and spent the past decade developing and upgrading the payment system while most countries focused on bank-based payment methods. Digital payment has become the major payment method in China due to the lack of financial foundation (Cheng et al. 2017). According to *China Third-party Payment Industry Research Report*, about 2913.99 trillion CNY has been transacted by using digital payment in China in 2020. Apart from the digital payment system, China also has a huge traditional banking system, including policy banks and commercial banks, which can be categorized as state-owned, joint-stock, city, and rural commercial banks (Wang et al. 2019). With a growing number of overlapped services between digital payment platforms and traditional commercial banks, commercial banks might be impacted by the development of digital payment platforms since the payment model of Chinese consumers has been changed (Yao et al. 2018).

Whether the impact exists and how traditional commercial banks are impacted by digital payment remains to be discussed and attracts researchers' interest. Although many scholars have done some related research, most of them remain to be at a theoretical level and failed to indicate the relationship between the development of digital payment and commercial banks in the long term. It is necessary to analyze whether the impact exists, and, if exists, how commercial banks were impacted by digital payment from a new perspective by using empirical methods.

2. Literature Review
Since the 21st century, the improvement in technology and the internet enables the application of digital payment in China. Currently, the digital payment system involves multiple digital payment technologies, including digital

payment platforms and gateway, such as UnionPay, electronic payment cards, such as Apple Pay, as well as mobile payments, such as Alipay and WeChat Pay, as so on (Tang et al. 2021). The innovation in the financial industry has an impact on financial services, banking, risk management, electronic business, etc. (Dong et al. 2019). Some scholars believe that the development in digital payment has caused more stress for commercial banks due to the intensified competition (Funk 2019), at the same time, some hold the view that the newly developed technology in payment enables traditional commercial banks to improve their services and productivity, as well as reduce operating cost (Srivastava 2014).

Profitability, which has been widely accepted to measure how banks perform, has been a hot topic in research. The determinants of profitability of commercial banks, which can be categorized as internal and external, have been analyzed and tested by scholars. Internal factors are usually depicted by bank-specific characters. Mostak Ahamed (2017) used the two-step system generalized method of moments (SYS-GMM) to examine bank-specific factors based on panel data of Indian banks. Income diversification and non-traditional sources of income of banks were proved to be associated with the profitability of banks. More specifically, extensive research papers show that the size of bank, capital adequacy, and costs are listed to be influential internal factors (Batten and Vo 2019, Athanasoglou et al. 2008). In addition to internal factors, macroeconomic and industry-specific characteristics have been defined as external factors by scholars. As for macroeconomic environment factors, tax rate, interest rate, as well as real GDP growth have been verified as determinants based on empirical analytics (Dietrich and Wanzenried 2011, Garcia and Martins 2016). The financial crisis, which leads to systemic risk in the economy, was treated as an external factor and tested (Garcia and Martins 2016, Guo and Shen 2016).

As one of the basic motivities of industrial evolution, technological innovation leads to industrial changes as well as economic structural changes (Schumpeter 2017). Commercial banks, as the traditional financial institution, are embracing the benefits from technological innovation and taking the risk from the competition with newly developed payment technology at the same time. On the one hand, the development of digital payment has been proved to be beneficial for the performance of commercial banks. Instead of competition, collaboration with digital payment is beneficial for banks to complement shortcomings, gain more customers, and increase profitability (Tobing and Wijaya 2020). Panel models were used to test the relationship between digital finance and traditional commercial banks (Dong et al. 2020) and the results showed that banking profitability can be increased by receiving more information and customers from digital payment applications. More than that, the demand and supply will be enlarged with the development of digital payment (Yao et al. 2018). On the other hand, some scholars hold the view that there is competition between commercial banks and digital payment, and the profitability of commercial banks was negatively impacted (Chen et al. 2020). A fixed-effect model was employed by Chen et al. (2020), and the result showed that digital payment had hurt banking profitability by decreasing the interest income of loans and increasing cost. The capital cost of commercial banks will also be increased by digital payment (Guo and Shen 2016). More than that, commercial banks take more risks because of the development in digital payment (Hou et al. 2016).

The efficiency, or productivity, of commercial banks, is another perspective to present the performance. To estimate the productivity and efficiency of commercial banks, DEA has been widely adopted as an empirical method by scholars (Tan and Floros 2013). The productivity of commercial banks is measured by how efficient banks will be using input, which is usually presented by the cost of banks, to generate output, which is usually represented by profitability ratios. Rostislav (2015) used the stochastic frontier analysis to calculate the inefficiency of profit and cost based on a panel dataset including data from 14 Czech commercial banks from 2000 to 2012, and the result showed that the interest rate had been one of the negative determinants of the efficiency. Fiordelisi et al. (2011) applied Granger causality test and the results showed that good capital structure had increased the efficiency of commercial banks.

Based on previous research, it is estimated that development in digital payment in which commercial banks are involved is beneficial because applying as well as collaborating with digital payment will help traditional banks to be more effective by sharing information and customers. On the other hand, the development in digital payment that commercial banks are not involved, or third-party digital payment, will hurt banking profitability by increasing the cost and competition. However, scholars hold a mixed view on the impact of digital payment on the bank efficiency (Zhao 2018). Their hypotheses have been tested at a theoretical level, but the relationship between commercial banks and the digital payment in the long term was failed to be indicated. In this way, it is necessary to analyze whether the impact does exist and how commercial banks have been impacted by the digital payment from a new perspective.

3. Methods

The impact of bank-involved digital payment and third-party payment on commercial banks based on panel dataset was tested in two perspectives, including profitability and productivity. Firstly, GMM was employed to examine whether the impact on profitability exists and whether the impact is positive or negative. Secondly, Malmquist Productivity Index (MPI) was employed to represent the growth in productivity of commercial banks, and Panel VAR was applied to test the long-term relationship between growth in digital payment and growth in productivity of commercial banks.

3.1 Systematic Generalized Method of Moments (SYS-GMM)

To test the effects of digital payment on commercial banks, methods based on linear regression were adopted. The fixed-effect model was used to test the effect of potential determinants, including internal factors and external factors. The systematic GMM model, which is widely adopted by scholars to analyze the determinants of commercial banks' profitability (Ahamed 2017, Dietrich and Wanzenried 2011) was employed to avoid endogeneity and take differences within banks into consideration.

Before employing GMM, a fixed panel data model was adopted to analyze the impact of digital payment on commercial banks. Designed for panel data containing cross-sectional dimension N and time series dimension T (Feng et al. 2020, Liu and He 2019), the fixed effects panel data model is based on linear regression and can be represented as Equation (1).

$$y_{it} = \alpha + x_{it}^{T}\beta + \mu_i + u_{it}, i \in \{1, \dots, N\}, t \in \{1, \dots, T\} \tag{1}$$

where i indexes the cross-sectional units, each commercial bank in this project, and t is the time series observation. y_{it} denotes the dependent variable, and μ_i denotes the time-invariant individual effect. x_{it} denotes the exogenous variables of dimension $p \times 1$ with slope parameters β. $\boldsymbol{u}_t = (u_{1t}, \dots, u_{Nt})^T$ for each $t \in \{1, \dots, T\}$, and it is assumed that $\boldsymbol{u}_t$'s is independently identically distributed.

Considering potential dynamic effects and endogeneity (Nkoumou Ngoa and Song 2021), many researchers started to use a dynamic panel model. There are two reasons why GMM should be employed for this project. Firstly, the dataset is short panel data, which means the number of commercial banks is larger than the number of years. Secondly, GMM helps to observe differences within banks that are caused by the change of time. To avoid potential endogenous problems, two methods have been widely adopted, namely the differential generalized moment method (DIF-GMM) and the systematic generalized moment method (SYS-GMM).

3.2 Malmquist Productivity Index (MPI)

Based on the panel dataset, which includes financial performance data of 81 commercial banks in China from 2013 to 2019, it is essential to evaluate productivity for each bank in each year and to consider the change in time. Based on the Malmquist productivity index (Malmquist 1953), the distance function $D(\cdot)$ was defined to calculate technical efficiency (TE). In addition to the distance function $D(\cdot)$, an oriented radical DEA model was adopted to calculate Malmquist Productivity Index (MPI) (Fare et al., 1994), where the MPI can be expressed as below using observations at time t and $t+1$:

$$MPI_I^t = \frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)} \tag{2}$$

$$MPI_I^{t+1} = \frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^t, y^t)} \tag{3}$$

where x is the input factor and y is the output factor, which indicates that x can produce y. I denotes the orientation of the MPI model.

The geometric mean of two MPI can be represented by Equation (4), which can be decomposed into input-oriented technical change (TECHCH) and input-oriented efficiency change (EFFCH) as given in Equation (5).

$$MPI_I^G = (MPI_I^t MPI_I^{t+1})^{\frac{1}{2}} = \left[\left(\frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)}\right) \cdot \left(\frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \tag{4}$$

$$MPI_I^G = (EFFCH_I)\cdot(TECHCH_I^G) = \left(\frac{D_I^{t+1}(x^{t+1},y^{t+1})}{D_I^t(x^t,y^t)}\right)\left[\left(\frac{D_I^t(x^t,y^t)}{D_I^{t+1}(x^t,y^t)}\right)\cdot\left(\frac{E_I^t(x^{t+1},y^{t+1})}{D_I^{t+1}(x^{t+1},y^{t+1})}\right)\right]^{\frac{1}{2}} \quad (5)$$

To evaluate the impact of digital payment, as technological innovation, on the productivity of commercial banks, the input-oriented technical change (TECHCH), which is widely used in different industries by scholars (Yu et al. 2016, Li et al. 2017, Oh and Heshmati 2010), was calculated.

3.3 Panel Vector Auto-Regression (Panel VAR)

Based on the time-series VAR model (Sims 1980), the penal VAR model (Holtz et al. 1988) has been introduced and has been widely used in economy-related research since it is designed for panel datasets. This empirical model can be used to capture the correlation or causality between variables as well as the effects of each exogenous variable on other variables (Shao et al. 2021). In addition to that, this model can also forecast by providing possibilities using impulse-response function and error decomposition variances (Leitão and Ferreira 2021), as a result, the long-term relationship between variables can be tested. Based on the features of the panel VAR model (Canova and Ciccarelli 2013), this empirical method can be employed for this project since it overcomes the endogeneity. Sigmund and Ferstl (2017) extended this model to allow for p lags of m endogenous variables, k predetermined variables, and n strictly exogenous variables. The extended PVAR model is a combination of a single equation by dynamic panel model (DPM) and a vector autoregressive model (VAR).

$$\boldsymbol{y}_{i,t} = \mu_i + \sum_{l=1}^{p} \boldsymbol{A}_l \boldsymbol{y}_{i,t-1} + \boldsymbol{B}\boldsymbol{x}_{i,t} + \boldsymbol{C}\boldsymbol{s}_{i,t} + \epsilon_{i,t} \quad (6)$$

$\boldsymbol{I}_m$ denotes an $m \times m$ identity matrix. $\boldsymbol{y}_{i,t} \in \mathbb{R}^m$ represents an $m \times 1$ vector of endogenous variables for the ith cross-sectional unit at time t, while $\boldsymbol{y}_{i,t-1} \in \mathbb{R}^m$ is an $m \times 1$ vector of lagged endogenous variables. Let $\boldsymbol{x}_{i,t-1} \in \mathbb{R}^k$ be an $k \times 1$ vector of predetermined variables and $\boldsymbol{s}_{i,t-1} \in \mathbb{R}^n$ be an $n \times 1$ vector of strictly exogenous variables for $s = 1, \ldots, T$.

4. Data Collection

Table 1. Descriptive statistics of profitability variables from 2013 to 2019

Variable		Formula	Minimum	Maximum	Mean	Std. Deviation
ROA	Return on assets	Ratio of net profit to total asset	-0.009	0.019	0.008	0.003
ROE	Return on equity	Ratio of net profit to shareholder's equity	-0.077	0.273	0.111	0.050
NIM	Net income margin	Ratio of net interest income to total asset	0.002	0.051	0.020	0.006
PF	Price of funds	Ratio of total interest expenses to total deposits and other short funding	0.902	7.116	2.508	0.726
PFA	Price of fixed assets	Ratio of other operating expenses to fixed assets	0.050	5.877	0.521	0.810
PL	Price of labor	Ratio of personnel expenses to total assets	0.002	0.030	0.006	0.003

Source from: *Orbis (https://orbis.bvdinfo.com/ip), annual report of commercial banks, and calculation*

Data of banks in China is mainly from the annual reports, which are collected by Orbis, and those financial indexes which are available on Orbis, a database website that provides information of more than 55,000 banking and financial institutions in different countries all over the world. According to different categories of commercial banks in China, annual reports of 81 commercial banks have been collected with periods from 2013 to 2019 and 9 financial indexes, including equity, fixed assets, loans, and so on, have been extracted. More than that, to analyze the impact of digital payment on commercial banks, variables representing the profitability of commercial banks, including return on assets (ROA), return on equity (ROE), and net income margin (NIM) have also been calculated. In addition to profitability, the cost of commercial banks (Table 1) is another category of variables to evaluate the performance of banks. Based on operating features, the cost of commercial banks can be represented by three variables (Bian, Wang, & Sun, 2015), namely the price of funds (PF), price of fixed assets (PFA), as well as the price of labor (PL).

Other internal variables which are also considered as determinants of profitability of commercial banks should also be calculated and involved as controlling variables. Firstly, the variable in terms of total assets is used to measure bank size (Dietrich and Wanzenried,2011). To avoid a wide range of total assets which may lead to instability and bias, the logarithm of total assets is employed for further analysis (Batten and Vo 2019, Yao and Song 2021). Secondly, the risk of banks is measured by equity over total assets, which shows whether a certain bank is well-capitalized or not (Garcia and Martins 2016). Thirdly, the operating cost of commercial banks can also be estimated by the ratio of operating expenses to total assets (Batten and Vo 2019).

4.2 Data of digital payment

Based on the scope of digital payment, the values to represent digital payment in China can be represented by different indicators, including transaction amount, transaction volume, number of users, and so on. The data used to perform digital payment in this paper is the amount of digital payment, including bank-involved digital payment and third-party payment) from 2013 to 2019 Table 2.

Table 2. Descriptive statistics of digital payment data from 2013 to 2019 (in trillion CNY)

	Year	Minimum	Maximum	Mean	Std. Deviation
Bank-involved digital payment	7	1075.16	2607.04	2044.90	580.96
Third-party payment	7	10.40	249.88	112.15	92.40

Source from: *China Payment System Development Report*

(1) Bank-involved digital payment (BDP)

Bank-involved digital payment, which refers to the payment or transaction via digital platforms involving bank accounts and serves as intermedia of transactions between commercial banks (Shen and Hou 2021), is gathered from the official reports named *China Payment System Development Report*, which is provided by the Chinese government and includes amount and volume of internet payment, fixed-line payment, mobile payment, and digital payment as a total number.

(2) Third-party payment (TTP)

The second variable of digital payment, third-party payment, is also from the official annual report, *China Payment System Development Report*. The difference between BDP and TTP is that TTP refers to the aggregated digital payment via payment institutions rather than involving debit or credit cards directly.

5. Results and Discussion

All three empirical methods are based on panel data and calculated by using STATA. The results of those methods indicate the relationship between digital payment, including bank-involved payment and third-party payment, and the performance of commercial banks, which is represented by profitability and productivity.

5.1 Numerical Results

Based on short panel data with a larger number of commercial banks compared to the number of years, systematic GMM was applied to avoid the potential endogenous problem. According to the outputs of GMM models (Table 3), System GMM models perform better than Difference GMM models due to the over-identification issues (Baum et al. 2003). In addition, based on the results of Hansen tests, the variables are valid since the models only have first-order correlation (Liu and He 2019). In this way, the system GMM model is suitable for this project. This result indicates that the bank-involved digital payment is beneficial to the profitability of commercial banks, and the impact of third-party digital payment is proved to be negative.

Table 3. Outputs of DIFF-GMM and SYS-GMM models

	Dependent variable: Profitability of commercial banks					
	ROA		ROE		NIM	
Variables	DIFF-GMM	SYS-GMM	DIFF-GMM	SYS-GMM	DIFF-GMM	SYS-GMM
First-lagged ROA	0.144 (0.110)	0.361 *** (0.104)				
Second-lagged ROA	-0.130 ** (0.066)	-0.096 (0.086)				
First-lagged ROE			0.378 *** (0.094)	0.584 *** (0.107)		
Second-lagged ROE			-0.081 (0.074)	-0.004 (0.113)		
First-lagged NIM					0.402 *** (0.101)	0.470 *** (0.090)
Second-lagged NIM					-0.103 (0.094)	-0.060 (0.062)
SIZE	-0.008 *** (0.003)	-0.000 (0.000)	-0.045 (0.034)	-0.010 ** (0.004)	-0.006 (0.005)	0.001 (0.001)
RISK	-0.041 (0.026)	0.017 (0.019)	-0.629 *** (0.243)	-0.175 (0.225)	0.036 (0.047)	-0.018 (0.030)
COST	-0.129 (0.212)	-0.3375** (0.142)	-3.501 * (2.025)	-3.099 ** (1.232)	0.241 (0.412)	0.195 (0.295)
LNBDP	0.010 *** (0.004)	0.007 * (0.004)	0.067 ** (0.030)	0.020 (0.034)	0.018 ** (0.010)	0.029 *** (0.009)
LNTPP	-0.000 (0.001)	-0.002 ** (0.001)	-0.010 (0.009)	-0.006 (0.007)	-0.001 (0.002)	-0.004 ** (0.001)
Constant	0.096 (0.061)	-0.037 (0.028)	0.594 (0.681)	0.156 (0.231)	-0.008 (0.120)	-0.219 *** (0.053)
Observations	561	561	561	561	561	561
Banks	81	81	81	81	81	81
Wald chi2	40.84	190.33	100.71	426.06	331.01	313.04
Sargan test (*p*-value)	0.018 (0.02)	66.523 (0.16)	38.416 (0.20)	61.156 (0.30)	49.786 (0.02)	64.937 (0.19)
AR(1) test (*p*-value)	-1.994 (0.04)	-2.607 (0.01)	-2.992 (0.00)	-3.232 (0.00)	-2.792 (0.01)	-3.172 (0.00)
AR(2) test (*p*-value)	-0.742 (0.46)	-0.937 (0.35)	0.151 (0.88)	-0.125 (0.90)	0.262 (0.79)	0.562 (0.57)

*Notes: ***, **, *: statistical significance at 1%, 5%, and 10% respectively. Robust standard errors are given in parentheses. Sargan test refers to the over-identification test for the restrictions in GMM estimation. AR(1) and AR(2) are tests for autocorrelation in differences.*

The SYS-GMM estimation results show that bank-involved digital payment has been tested to be beneficial to the performance of commercial banks and the impact of third-party digital payment has been negative. For ROA, which is listed in the second column, the first-lagged ROA has been influential to the current ROA, and the impact of cost is negative. For ROE, as shown in the fourth column, the effect is not significant. However, the first-lagged ROE, size of banks, and cost of banks have a significant impact on the current ROE. Lastly, for NIM, the increase in the bank-involved digital payment would cause an increase in NIM, however, third-party payment harms NIM. To evaluate the productivity of commercial banks, the input-oriented technical change (TECHCH) was calculated by setting three variables of cost as input and profitability as output Table 4.

Table 4. Descriptive statistics of MPI of commercial banks by categories from 2013 to 2019

	Count	Minimum	Maximum	Mean	Std. Deviation
State-owned banks	36	0.890	1.261	1.049	0.099
Joint-stock banks	60	0.800	1.806	1.124	0.211
City commercial banks	228	0.478	2.959	1.063	0.241
Rural commercial banks	90	0.585	1.752	1.043	0.190
Foreign commercial banks	72	0.721	1.696	1.058	0.183
Total	486	0.478	2.959	1.065	0.213

To analyze the impact of digital payment on the productivity efficiency of commercial banks, variables of digital payments should also be represented in terms of growth rate Table 4, which should be the same as the Malmquist productivity index (MPI), which is calculated by the ratio of previous value (year $t-1$) to the current value (year t).

$$Growth\ in\ Digital\ Payment_I^{t+1} = \frac{Digital\ Payment_I^{t+1}}{Digital\ Payment_I^{t}} \tag{7}$$

where I denotes the digital payment variables, bank-involved digital payment, or third-party payment, t denotes the year.

Time series variables should be stationary based on the assumption of impulse response function (Yao et al., 2018). The stationarity of three variables should be tested before the panel VAR model. For panel variable, growth in productivity (MPI), of 81 commercial banks from 2014 to 2019, LLC and IPS were employed, and for time-series, the Augmented Dickey-Fuller (ADF) test method was used. The results indicate that all these three variables are statistically stationary. In addition to the stationary test, the cointegration test should be employed to exam whether there is a cointegration relationship between variables in the dataset. To test the cointegration, three methods suitable for panel data have been used, namely the Kao test (Kao 1999), Pedroni test (Pedroni 1999), and Westerlund test (Westerlund 2005). According to the results of all these three tests, the null hypothesis, which indicates that there is no cointegration, was rejected at a 5% level Table 5.

Table 5. Cointegration test on a panel dataset

Test method		t-Statistic	*p*-value
Kao test	Modified Dickey-Fuller t	2.003	0.023
	Dickey-Fuller t	-14.989	0.000
	Augmented Dickey-Fuller t	-64.590	0.000
	Unadjusted modified Dickey-Fuller t	-6.118	0.000
	Unadjusted Dickey-Fuller t	-21.597	0.000
Pedroni test	Modified Phillips-Perron t	7.793	0.000
	Phillips-Perron t	-20.228	0.000
	Augmented Dickey-Fuller t	-227.425	0.000
Westerlund test	Variance ratio	-3.041	0.001

Since the different number of lag intervals will cause a difference in the results of the panel VAR model, the number of lag intervals should be selected by minimizing the AIC, BIC, and HQIC. In this way, 1 is chosen to be the number of lag intervals. After testing and selecting the number of lag intervals, the result of the panel VAR model was generated Table 6. Based on the result, the effect of growth in bank-involved digital payment on the growth in productivity of commercial banks is significantly positive, and the effect of growth in third-party payment is significantly negative.

Table 6. Result of panel VAR model

	GBDP	GTPP	MPI
First-lagged GBDP	-1.486 *** (0.171)	1.233 *** (0.197)	4.017 * (2.114)
First-lagged GTPP	0.303 *** (0.014)	0.357 *** (0.021)	-0.527 ** (0.2536)
First-lagged MPI	-0.028 *** (0.007)	-0.008 (0.007)	0.114 (0.095)
AIC	-8.560		
BIC	-5.620		
HQIC	-7.387		

Although growth in digital payment is significantly related to growth in productivity of commercial banks, it doesn't indicate a causality link between those pairwise variables (Yao et al. 2018). To verify the causality relationship, the Granger causality test was applied Table 7. According to the result of the Granger causality test, the growth in bank-involved digital payment has a causality link with growth in productivity of commercial banks. However, growth in third-party digital payment is proved to be unable Granger cause growth in productivity.

Table 7. Granger causality test on variables of panel VAR

Null hypothesis	Chi2	Prob > Chi2
Growth in bank-involved digital payment		
GBDP does not Granger cause GTPP	447.09	0.000
GBDP does not Granger cause MPI	16.978	0.000
Growth in third-party payment		
GTPP does not Granger cause GBDP	39.149	0.000
GTPP does not Granger cause MPI	1.400	0.237

5.2 Graphical Results

Based on the results of the cointegration test, the time-series variables in the panel VAR model are indicated to be cointegrated. As a result, the results identified the relationship between variables exists in a long run. To reveal the long-term relationship, the Impulse response function was employed Figure 1.

From the visualized results of the impulse response function, growth in digital payment is shown to be influential on the growth in productivity of traditional commercial banks at an initial stage. Growth in bank-involved digital payment will lead to an increase in productivity, which means the effect is positive overall. In contrast, growth in third-party digital payment will restrain the growth in productivity in commercial banks in a long term.

The empirical results of the panel VAR model show that the development in digital payment has a long-term impact on the productivity of commercial banks. According to the panel VAR model, the first-lagged growth in bank-involved digital payment has a significant positive correlation with the MPI of commercial banks, and first-lagged third-party payment has a negative correlation with MPI. More than that, the result of the impulse-responses model, the growth in digital payment, and the productivity of commercial banks have long-term correlations.

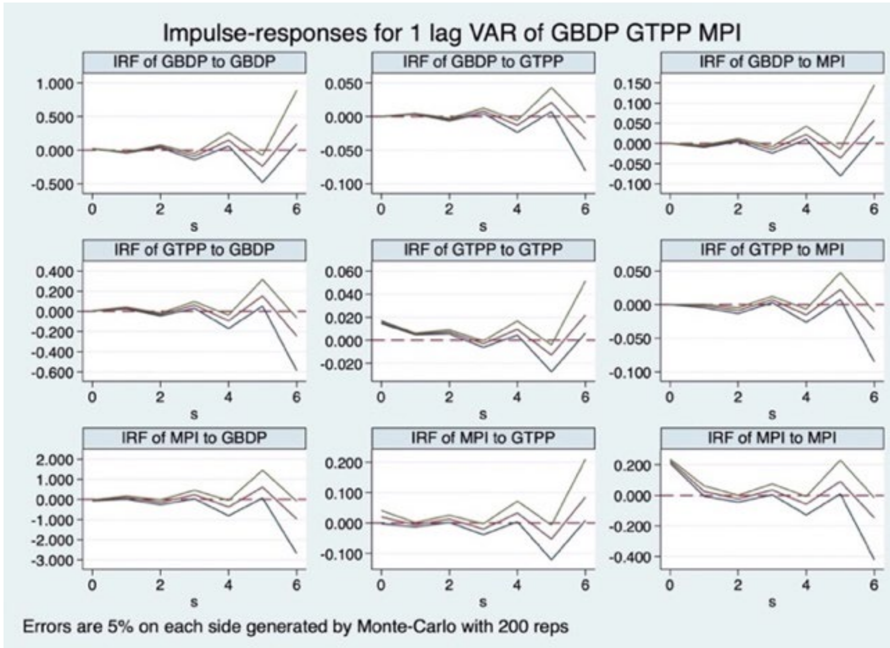

Figure 1. Impulse-responses for 1 lag VAR

6. Conclusion

The impact of digital payment on traditional commercial banks has been proved by using empirical methods, and the results of the empirical analysis indicate the hypothesis as well as demonstrate that the impact of digital payment on commercial banks can be analyzed by profitability as well as productivity. However, the impact cannot be concluded as simply positive or negative. According to the type of digital payment platforms, bank-involved digital payment and third-party digital payment have different effects on commercial banks. The development of digital payment poses opportunities as well as risks for traditional commercial banks. If commercial banks realize the benefits brought by the change in payment system, traditional banks can collaborate with digital payment and increase their profitability and efficiency. However, there are potential risks caused by the fierce competition with newly developed technology.

To collaborate with digital payment, traditional commercial banks should employ and embrace new technology which can help them reduce cost, increase efficiency, and control risks (Dong et al. 2020). In addition to the benefits of technology upgrades, the information from digital payment and users of digital payment platforms can be shared with commercial banks since bank-involved digital payment requires a bank account. As a result, commercial banks can complement their shortcomings. Currently, the rapid growth in e-Commerce promotes the development of digital payment. Large digital payment platforms, such as Alipay and WeChat Pay, have a strong customer base and advanced technology, such as biological recognition, to ensure security. Collaborating with such companies can help the reformation within traditional commercial banks. On the other hand, those digital payment platforms which don't need bank participation bring more challenges for commercial banks by providing higher interest rates of deposits and lower interest rates for loans. As a result, competition leads to a loss in customers of commercial banks due to attractive interest rates and better services provided by third-party digital payment platforms. To be better prepared for such challenges posed by third-party digital payment platforms, commercial banks should improve their competitiveness to maintain their customers by providing better services and more attractive interest rates.

In conclusion, according to the results of these empirical methods, traditional commercial banks should be open to new technology and keep improving competitiveness under the current situation that digital payment is becoming more and more popular. More than that, traditional commercial banks must play their strengths. For example, commercial banks are more trustworthy compared to internet finance companies. In this way, commercial banks can increase their profitability and be more efficient.

References

Ahamed, M. M., Asset quality, non-interest income, and bank profitability: Evidence from Indian banks. *Economic Modelling*, vol. 63, pp. 1-14, 2017.

Athanasoglou, P. P., Brissimis, S. N., and Delis, M. D., Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions & Money*, vol. 18, no. 2, pp. 121-136, 2008.

Batten, J., and Vo, X. V., Determinants of bank profitability-evidence from Vietnam. *Emerging Markets Finance & Trade*, vol. 55, no. 6, pp. 1417-1428, 2019.

Baum, C. F., Schaffer, M. E., and Stillman, S., Instrumental variables and GMM: Estimation and testing. *The Stata Journal*, vol. 3, no. 1, pp. 1-31, 2003.

Bian, W. L., Wang, X. N., and Sun, Q. X., Non-interest income, profit, and risk efficiencies: Evidence from commercial banks in China. *Asia-Pacific Journal of Financial Studies*, vol. 44, no. 5, pp. 762-782, 2015.

Chen, Z., Li, K., and He, L.-Y., Has internet finance decreased the profitability of commercial banks?: Evidence from China. *Emerging Markets Finance & Trade*, vol. 56, no. 13, pp. 3015-3032, 2020.

Cheng, Y. W., Hsu, S. Y., and Lo, C. P., Innovation and imitation: competition between the US and China on third-party payment technology. *Journal of Chinese Economic and Foreign Trade Studies*, vol. 10, no. 3, pp. 252-258, 2017.

Dietrich, A., and Wanzenried, G., Determinants of bank profitability before and during the crisis: evidence from Switzerland. *Journal of International Financial Markets, Institutions & Money*, vol. 21, no. 3, pp. 307-327, 2011.

Dong, J., Yin, L., Liu, X., Hu, M., Li, X., and Liu, L., Impact of internet finance on the performance of commercial banks in China. *International Review of Financial Analysis*, vol. 72, 2020.

Fare, R., Grosskopf, S., Norris, M., and Zhang, Z., Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review*, vol. 84, no. 1, pp. 66-83, 1994.

Feng, L., Ding, Y., and Liu, B., Rank-based tests for cross-sectional dependence in large (N, T) fixed effects panel data models. *Oxford Bulletin of Economics and Statistics*, vol. 82, no. 5, pp. 1198-1216, 2020.

Fiordelisi, F., Marques-Ibanez, D., and Molyneux, P., Efficiency and risk in European banking. *Journal of Banking & Finance*, vol. 35, no. 5, pp. 1315-1326, 2011.

Funk, A. S., From informal finance to internet finance in China. *Crowdfunding in China*. pp. 95-147, 2019.

Garcia, M. T. M., and Martins, J. P. S., Internal and external determinants of banks' profitability: The Portuguese case. *Journal of Economic Studies (Bradford)*, vol. 43, no. 1, pp. 90-107, 2016.

Guo, P., and Shen, Y., The impact of Internet finance on commercial banks' risk taking: Evidence from China. *China Finance and Economic Review*, vol. 4, no. 1, pp. 1-19, 2016.

Hou, X., Gao, Z., and Wang, Q., Internet finance development and banking market discipline: Evidence from China. *Journal of Financial Stability*, vol. 22, pp. 88-100, 2016.

Huang, Q., de Haan, J., and Scholtens, B., Analysing systemic risk in the Chinese banking system. *Pacific Economic Review (Oxford, England)*, vol. 24, no. 2, pp. 348-372, 2019.

Kao, C., Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, vol. 90, no. 1, pp. 1-44, 1999.

Li, Z., Crook, J., and Andreeva, G., Dynamic prediction of financial distress using Malmquist DEA. *Expert Systems with Applications*, vol. 80, pp. 94-106, 2017.

Liu, H., and He, Q., The effect of basic public service on urban-rural income inequality: a sys-GMM approach. *Ekonomska Istraživanja*, vol. 32, no. 1, pp. 3211-3229, 2019.

Malmquist, S., Index numbers and indifference surfaces. *Trabajos de Estadistica*, vol. 4, pp. 209-242, 1953.

Ngoa, G. B. N., and Song, J. S., Female participation in African labor markets: the role of information and communication technologies. *Telecommunications Policy*, vol. 45, no. 9, 2021.

Oh, D., and Heshmati, A., A sequential Malmquist–Luenberger productivity index: environmentally sensitive productivity growth considering the progressive nature of technology. *Energy Economics*, vol. 32, no. 6, pp. 1345-1355, 2010.

Oney, E., Guven, G. D., and Rizvi, W. H., The determinants of electronic payment systems usage from consumers' perspective. *Ekonomska Istraživanja*, vol. 30, no. 1, pp. 394-415, 2017.

Pedroni, P., Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics*, vol. 61, no. 4, pp. 653-670, 1999.

Staněk, R., Determinants of bank efficiency: Evidence from Czech banking sector. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, vol. 63, no. 3, pp. 1005-1011, 2015.

Schumpeter, J. A., The fundamental phenomenon of economic development. *The Theory of Economic Development*, vol. 1, pp. 57-82, 2017.

Shen, W., and Hou, L., China's central bank digital currency and its impacts on monetary policy and payment competition: Game changer or regulatory toolkit? *The Computer Law and Security Report*, vol. 41, 2021.

Srivastava, A., The status and impact of E-finance on developing economy. *Golden Research Thoughts*, vol. 3, no. 11, 2014.

Tan, Y., and Floros, C., Risk, capital and efficiency in Chinese banking. *Journal of International Financial Markets, Institutions & Money*, vol. 26, pp. 378-393, 2013.

Tang, Y. M., Chau, K. Y., Hong, L., Ip, Y. K., and Yan, W., Financial innovation in digital payment with WeChat towards electronic business success. *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 16, no. 5, pp. 1844-1861, 2021.

Tobing, J. D. T., and Wijaya, C., The effect of Peer-to-Peer lending and third-party payments on conventional commercial bank profitability in Indonesia. *International Journal of Management*, vol. 11, no. 5, 2020.

Wang, Z., Xie, N., and Jin, Y., Do loan loss provisions affect the credit fluctuations in China's banking system? *Emerging Markets Finance & Trade*, vol. 55, no. 11, pp. 2425-2436, 2019.

Westerlund, J., New simple tests for panel cointegration. *Econometric Reviews*, vol. 24, no. 3, pp. 297-316, 2005.

Yao, M., Di, H., Zheng, X., and Xu, X., Impact of payment technology innovations on the traditional financial industry: A focus on China. *Technological Forecasting & Social Change*, vol. 135, pp. 199-207, 2018.

Yao, T., and Song, L., Examining the differences in the impact of Fintech on the economic capital of commercial banks' market risk: Evidence from a panel system GMM analysis. *Applied Economics*, vol. 53, no. 23, pp. 2647-2660, 2021.

Yu, C., Shi, L., Wang, Y., Chang, Y., and Cheng, B., The eco-efficiency of pulp and paper industry in China: An assessment based on slacks-based measure and Malmquist–Luenberger index. *Journal of Cleaner Production*, vol. 127, pp. 511-521, 2016.

Yu, H. C., Hsi, K. H., and Kuo, P. J., Electronic payment systems: An analysis and comparison of types. *Technology in Society*, vol. 24, no. 3, pp. 331-347, 2002.

Zhang, D., Cai, J., Liu, J., and Kutan, A. M., Real estate investments and financial stability: Evidence from regional commercial banks in China. *The European Journal of Finance*, vol. 24, no. 16, pp. 1388-1408, 2018.

Zhao, S., Research on the impact of internet finance on the efficiency of Chinese commercial banks. *American Journal of Industrial and Business Management*, vol. 8, no. 4, 2018.

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