# Does Fintech Help Financial Resources Flow to the Real Economy? -- From the Perspective of Total Factor Productivity and Capital Risk of Banks

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**Abstract:** Through the analysis of bank data from 2011 to 2019, this paper studies the impact of fintech development on the real economy from the perspective of enterprise financing, and its mechanism from the perspectives of total factor productivity and bank risk. The empirical results show that the fintech development will not significantly increase supply of bank loans to the real economy. The possible reason for it is that in the early period of development, fintech promotes bank total factor productivity to increase the supply of loanable funds, while it also improves the bank's capital risk and reduces its willingness to support the real economy. And in the late stage, financial development has the opposite result, also result in fintech does not increase banks' support for the real economy. In addition, the heterogeneity analysis indicates that fintech has different transmission mechanisms for state-owned banks and non-state-owned banks to serve the real economy and finally produces different effects. Fintech can significantly improve the credit support of state-owned banks to the real economy, but has no significant impact on non-state-owned banks.

## 1. Introduction

At present, China's financial resources are "loose money and tight capital"[1](Cai Zexiang, Wu Xueqiang, 2016). Although execute more prudent monetary policy, the central bank increases the money supply, but the real economy enterprise financing is still relatively difficult, is common micro, small and medium enterprises "financing difficulties" and "financing your" problem, largely because of a greater part of the money into the financial sector, real estate, etc. In the virtual economy, the real economy enterprises win less discount. As an emerging technology emerging in recent years, fintech can effectively solve the problem of information asymmetry, improve the quality of financial service supply and the efficiency of resource allocation, and have the possibility to solve the financing problem of enterprises. At the same time, as China's capital market is still underdeveloped, for the majority of small and medium-sized enterprises, the proportion of funds obtained through direct financing channels such as stocks and bonds is small, so Banks play an important role in the financing process of enterprises. Therefore, it is of great practical significance to study the influence of fintech on the real economy from the perspective of enterprise financing through bank financing.

The innovations and possible marginal contributions of this paper are mainly in the following aspects: First, this paper focuses on studying the role of fintech in the real economy from the perspective of enterprises financing through Banks, which has certain practical significance on how to better play the supporting role of Banks and other financial institutions in the real economy; Secondly, based on the practice of Shen Yue and Guo Pin (2015) [5], this paper constructed the fintech index through text mining, quantified the recent development status of fintech in Banks, and improved the applicability of the index. Thirdly, on the basis of the previous studies, this paper makes a further analysis of the mechanism of fintech from the perspectives of bank efficiency and risk, so as to indicate the possible future key research directions for fintech to better play its role. Fourthly, based on the empirical test results, this paper puts forward policy Suggestions on how to better play the role of fintech in serving the real economy, which is of great reference significance for solving the problem of "de-materialization to virtual" of financial resources in China.

## 2. Variable selection and model setting

### 2.1 Variable selection and index construction

#### 2.1.1 Explained variable: the loan scale of the real economy RED

In order to measure the strength of Banks' support for the real economy, this paper selects the total loans of Banks to enterprises in the real economy (excluding enterprises in the financial industry and real estate industry) as the proxy variable of the loan scale of the real economy.

#### 2.1.2 Important explanatory variable: Fintech index

The existing literature on the measurement of fintech level mainly includes two methods: One is the Internet finance index based on "text mining" proposed by Shen Yue and Guo Pin (2015) [5] from the perspective of financial function. The index calculates the technology application level of Banks through the statistics of keyword frequency in Baidu News. One is the digital Financial Inclusion Index established by the Research Center for Digital Finance of Peking University and the joint research group of Ant Financial services, which focuses on measuring the overall development level of fintech in different regions. Since this paper takes the transmission channel Banks of fintech and real economy as the main research sample, the Internet finance index is selected as the measurement index of fintech in this paper, and the text mining method and factor analysis method are used to construct it. The specific steps are as follows:

The first step is to pre-crawl the fintech related news in Baidu News. Since fintech involves many dimensions and keywords vary greatly, in order to determine the most accurate keyword database, "fintech" + "bank" is searched as keywords, and Python web crawler technology is used to obtain the text of news headlines.

Second, natural language processing (NLP) was used to extract the highest frequency keywords. For the obtained news title text, after removing the duplicate news, the Jieba analysis toolbox of Python was used to extract keywords and weights using the TF-IDF algorithm, and five keywords with the highest frequency were obtained: big data, artificial intelligence, cloud computing, blockchain and Internet of Things.

Table 1 Fintech word frequency table from 2011 to 2019

| Year | Big data | Artificial intelligence | Cloud computing | Block chain | Web of things |
|---|---|---|---|---|---|
| *2019* | 1397 | 1195 | 868 | 1175 | 731 |
| *2018* | 929 | 938 | 599 | 987 | 464 |
| *2017* | 603 | 539 | 301 | 478 | 288 |
| *2016* | 396 | 124 | 145 | 127 | 172 |
| *2015* | 221 | 56 | 114 | 28 | 121 |
| *2014* | 105 | 23 | 47 | 23 | 54 |
| *2013* | 51 | 53 | 48 | 33 | 39 |
| *2012* | 12 | 17 | 31 | 19 | 27 |
| *2011* | 26 | 13 | 37 | 8 | 29 |
| *Sum* | 3740 | 2958 | 2190 | 2878 | 1925 |

The third step is to calculate the keyword frequency by year. After get keywords library, again to crawl baidu news, to improve the precision of the method of drawing (2020) [6] Jin Hongfei, bank name and keyword match (such as "the bank of China" and "big data") to retrieve, including bank name full name, article 13691 not repeat news headlines, statistical results are shown in table 1, the clear financial technology word frequency in the table showing a rising trend year by year, and no slow speed in recent years, show that bank overall level of science and technology constantly improve and still has great potential to rise. Horizontal comparison shows that big data is still the most popular relevant keywords, while artificial intelligence and blockchain, as rising stars, have been gradually organically combined with banking business. At the same time, the five fintech technologies as a whole are in equilibrium.

The fourth step is to use factor analysis to calculate fintech indicators. Subsequently, the comprehensive score of factor analysis was calculated for the above news headlines. In this paper, Matlab R2018a software was used to calculate the factor score of sub-banks from year to year in the way of pre-test -- construction factor variable -- factor rotation -- calculation variable score, and it was used as the measurement index of fintech level.

### 2.1.3 Intermediary variable: total factor productivity of Banks-TFPCH

(1) DEA measure method

Bank total factor productivity measures the changes of bank efficiency in different times from the dynamic perspective. Currently, total factor productivity measurement methods based on frontier analysis mainly include two types: one is data envelope-analysis method (DEA) based on non-parametric operations, and the other is stochastic frontier analysis method (SFA) based on parametric operations. Because the SFA method presupposes the efficiency boundary function, the measurement of total factor productivity may be deviated. However, DEA method does not need to set the production function in advance, which reduces the subjective error and has low requirements on sample size (Yuan Xiaoling, Zhang Baoshan, 2009[7]). Therefore, considering the special production and operation mode, special production function and sample size of Banks, this paper chooses DEA method to measure.

(2) Malmquist index model

Initially proposed by Malmquist (1953)[8], the Malmquist index was used to construct the consumption quantity function. Scholars such as Fare (1992) [9] combined it with DEA method to measure production efficiency, and this method has been widely used in the academic circle. The Malmquist index is constructed as follows.

Taking the t period technique $T^t$ as a reference, the Malmquist index based on the output angle can be expressed as:

$$M_0^t(x^{t+1},y^{t+1},x^t,y^t)=\frac{d_0^t(x^{t+1},y^{t+1})}{d_0^t(x^t,y^t)}$$

Similarly, taking t+1 technique $T^{t+1}$ as a reference, the Malmquist index based on the output angle can be expressed as:

$$M_0^{t+1}(x^{t+1},y^{t+1},x^t,y^t)=\frac{d_0^{t+1}(x^{t+1},y^{t+1})}{d_0^{t+1}(x^t,y^t)}$$

In order to prevent the difference caused by the random selection of periods, the geometric average values of t period and T +1 period were taken as a measure of the productivity changes from T period to T +1 period. The improved Malmquist index is as follows:

$$M_0^{t,t+1}(x^{t+1},y^{t+1},x^t,y^t)=\left[\frac{d_0^t(x^{t+1},y^{t+1})}{d_0^t(x^t,y^t)}\times\frac{d_0^{t+1}(x^{t+1},y^{t+1})}{d_0^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}}$$

$(x^{t+1},y^{t+1})$ and $(x^t,y^t)$ represent the input and output vectors of t+1 and T; $d_0^t$ and $d_0^{t+1}$ are the distance functions of input-output combinations at t and T +1 respectively. They represent the reciprocal of the maximum possible expansion multiples of a given input-output vector under the technical conditions of this period, which can be solved by the following linear programming:

$$\left[d_0^t(x^t,y^t)\right]^{-1}=Max_{\phi,\lambda}\phi\ s.t.\begin{cases}-\phi y_i^t+y^t\lambda\ge 0\\ x_i^t-x^t\lambda\ge 0\\ \lambda\ge 0\end{cases}$$

$$\left[d_0^{t+1}(x^{t+1},y^{t+1})\right]^{-1}=Max_{\phi,\lambda}\phi \ s.t.\begin{cases}-\phi y_i^{t+1}+y^{t+1}\lambda\ge 0\\ x_i^{t+1}-x^{t+1}\lambda\ge 0\\ \lambda\ge 0\end{cases}$$

By substituting the above distance function into the formula, the Malmquist exponent under the DEA method can be obtained. The Malmquist index can be further transformed into the comprehensive technical efficiency change index and the technical progress index under the condition of constant return to scale. The decomposition results are as follows.

$$M_c^{t,t+1}(x^{t+1},y^{t+1},x^t,y^t)=\frac{d_c^{t+1}(x^{t+1},y^{t+1})}{d_c^t(x^t,y^t)}\left[\frac{d_c^t(x^{t+1},y^{t+1})}{d_c^t(x^t,y^t\,|\,C)}\times\frac{d_c^{t+1}(x^t,y^t)}{d_c^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}}$$

Among them, the comprehensive technical efficiency change index can be further decomposed into pure technical efficiency index and scale efficiency index, and the decomposition results are as follows.

$$M_{v,c}^{t,t+1}=\frac{d_v^{t+1}(x^{t+1},y^{t+1})}{d_v^t(x^t,y^t)}\times\left|\frac{d_v^t(x^t,y^t)}{d_c^t(x^t,y^t)}\Big/\frac{d_v^{t+1}(x^{t+1},y^{t+1})}{d_c^t(x^{t+1},y^{t+1})}\right|\times\left[\frac{d_c^t(x^{t+1},y^{t+1})}{d_c^t(x^t,y^t\,|\,C)}\times\frac{d_c^{t+1}(x^t,y^t)}{d_c^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}}$$
$$=PECH\times SECH\times TECHEH$$

(3) Input-output index design

The selection methods of production function indicators include "production method", "intermediary method" and "income and expenditure method". Compared with "production method" and "income and expenditure method", "intermediary method" can better reflect the financing function of Banks as financial institutions, and the data of bank deposits and loans is relatively easy to obtain (CAI Yuezhou and Guo Meijun, 2009[10]). Therefore, this paper adopts the "intermediary method" to select input-output indicators. Total assets ($X1$), annual operating expenses ($X2$) and total deposits ($X3$) of Banks at the end of the year are selected as input variables, while total loans ($Y1$) and annual pre-tax profits ($Y2$) are selected as output variables.

(4) Total factor productivity measurement results

Using Win4DEAP software, Malmquist index model was used to measure the DEA of 152 Banks, and the statistical results of annual comprehensive technical efficiency change index EFFCH, technical progress index TECHEH, pure technical efficiency PECH, scale efficiency index SECH and total factor productivity TFPCH were shown in Table 2.

Table 2 Changes and decomposition of annual Malmquist index from 2011 to 2019

| *Year* | *EFFCH* | *TECHEH* | *PECH* | *SECH* | *TFPCH* |
|---|---|---|---|---|---|
| *2019* | 1.022 | 0.964 | 0.968 | 1.055 | 0.987 |
| *2018* | 1.167 | 0.892 | 1.140 | 1.026 | 1.029 |
| *2017* | 1.220 | 0.840 | 1.077 | 1.148 | 0.998 |
| *2016* | 0.712 | 1.445 | 0.830 | 0.866 | 1.021 |
| *2015* | 0.996 | 0.973 | 1.004 | 0.993 | 0.969 |
| *2014* | 0.979 | 1.066 | 0.984 | 0.996 | 1.046 |
| *2013* | 1.015 | 0.974 | 1.019 | 0.996 | 0.989 |
| *2012* | 1.118 | 0.909 | 1.091 | 1.028 | 1.015 |
| *2011* | 1.627 | 0.588 | 1.198 | 1.382 | 0.960 |
| *Mean* | 1.081 | 0.980 | 1.031 | 1.044 | 1.004 |

**2.1.4 Intermediary variable: bank capital risk**

The existing literature on bank risk measurement mainly includes capital asset ratio, loan loss reserve ratio and risk asset ratio. Referring to the practice of Guo Pin and Shen Yue (2015) [11], this paper selects the capital asset ratio of Banks as the proxy variable to measure the capital risk of Banks.

### 2.1.5 Control variables

Because the scale of Banks' loans to the real economy is affected by both macroeconomic factors and individual bank factors. Therefore, this paper refers to the practice of Jin Hongfei (2020) [6], selecting the GDPr indicators of economic development level, the level of inflation CPI index, the marketization of interest rate Policy Policy index as the control of macroeconomic variables, the ROA indicators of bank profitability, operation efficiency of cost to income ratio Costinc index, whether listed IPO index variables as control bank individual factors.

## 2.2 Model setting

The research of Liu Yuan et al. (2018) [2] shows that there may be a non-linear relationship between the effects of fintech on the real economy. Therefore, this paper introduces the quadratic term of fintech. At the same time, because the loan amount provided by Banks to the real economy is affected by individual factors and macro background of Banks, two-way fixed effect model is established to fix individual and time difference. The model construction method is as follows:

$$RED_{i,t}=\alpha+\beta_1 Fintech_{i,t}+\beta_2 Fintech_{i,t}{}^2+\gamma\sum X_{i,t}+u_i+v_t+\varepsilon_{i,t}$$

In the model, RED represents the explained variables bank lending to the real economy, Fintech represents the period of the bank's financial technology development index, X represents the control variables (the level of economic development, inflation levels, the marketization of interest rate policy, whether listing, bank profitability, management efficiency of the bank), u on behalf of the bank individual effect, v represent the time effect.

At the same time, in order to study the transmission mechanism of fintech for Banks to support the real economy, this paper further introduces two variables of Banks' total factor productivity TFPCH and banks' risk Risk, and constructs the following model:

$$TFPCH_{i,t}=\alpha+\beta_1 Fintech_{i,t}+\beta_2 Fintech_{i,t}^2+\gamma\sum X_{i,t}+u_i+v_t+\varepsilon_{i,t}$$

$$Risk_{i,t}=\alpha+\beta_1 Fintech_{i,t}+\beta_2 Fintech_{i,t}^2+\gamma\sum X_{i,t}+u_i+v_t+\varepsilon_{i,t}$$

# 3. Sample selection and descriptive statistics

## 3.1 Sample selection and data sources

Considering the representativeness of samples and the availability of data, 152 Chinese Banks were selected as research samples in this paper, including 5 large commercial Banks, 12 joint-stock commercial Banks, 91 urban commercial Banks and 44 rural commercial Banks. The sample interval is selected from 2011 to 2019, and the bank data and macro data are from CSMAR database.

Table 3 Descriptive statistics

| Variables | Mean | Std | Max | Min | N |
|---|---|---|---|---|---|
| RED ($\times 10^{12}$) | 18.071 | 534.827 | 16354.300 | 0.000 | 935 |
| Fintech | 0.102 | 0.970 | 6.496 | -0.515 | 935 |
| TFPCH | 1.004 | 0.184 | 3.027 | 0.220 | 935 |
| Risk | 66.132 | 52.501 | 323.080 | 3.320 | 935 |
| GDPr (%) | 7.320 | 0.952 | 9.000 | 6.100 | 935 |
| CPI | 102.371 | 1.075 | 105.390 | 101.440 | 935 |
| Policy | 0.548 | 0.498 | 1 | 0 | 935 |
| ROA | 0.010 | 0.004 | 0.029 | 0.000 | 935 |
| IPO | 0.201 | 0.401 | 1 | 0 | 935 |
| Costinc | 0.551 | 0.151 | 0.998 | 0.010 | 935 |

### 3.2 Descriptive statistics

Table 3 lists the descriptive statistics of the important variables in the model. The average ratio of loans provided by Banks to the real economy is 18.071, and the range is wide. The fintech index of Banks is 0.102, the mean of total factor productivity is 1.004, the average risk level of Banks is 66.132, and the dispersion degree is large. The mean value and standard deviation of other variables are all distributed at the normal level.

## 4. Empirical test

### 4.1 Basic regression analysis

As shown in Table 4 (1) and (2), there is no significant correlation between the primary and secondary items of fintech and the loans of Banks to the real economy when only the total loans to the real economy are considered. At the same time, it can be seen from the columns (3) and (4) of Table 4 that the above conclusion is still valid after the introduction of control variables, which indicates that the development of fintech does not have a significant impact on the support of Banks for the real economy. Possible reasons for our country is still in its early financial science and technology development, the bank to use the technology of financial credit evaluation system is not perfect, cause money through layer upon layer, gradually into the book value is higher than the actual value, the asset price inflation of virtual economy, and make the entity economic financing difficulties, financing your problem has not been resolved. The coefficients of the remaining control variables were broadly in line with expectations.

Table 4 The impact of fintech on the amount of loans in the real economy

| | (1)RED | (2) RED | (3) RED | (4) RED |
|---|---|---|---|---|
| Fintech | -18.279<br>(32.399) | -91.331<br>(66.918) | -24.272<br>(32.782) | -107.735<br>(67.016) |
| $Fintech^2$ | | 18.478<br>(14.756) | -15.383<br>(219.490) | 21.171<br>(14.830) |
| CPI | | | -15.329<br>(219.490) | -12.598<br>(219.350) |
| GDPr | | | -37.411<br>(220.784) | -32.705<br>(220.660) |
| IPO | | | 21.325<br>(105.636) | 34.206<br>(105.950) |
| Policy *Policy* | | | -206.119<br>(1258.842) | -196.232<br>(1258.014) |
| Costinc | | | 75.458<br>(215.710) | 105.737<br>(216.606) |
| ROA | | | $30089.260^{***}$<br>(10778.350) | $31311.57^{***}$<br>(10805.07) |
| Year | Fixed | Fixed | Fixed | Fixed |
| Unity | Fixed | Fixed | Fixed | Fixed |
| N | 935 | 935 | 935 | 935 |
| $R^2$ | 0.010 | 0.008 | 0.018 | 0.017 |

### 4.2 Mechanism of action

The supply of loans to the real economy depends on the scale of loanable funds and the willingness of Banks to use loanable funds to support the real economy. Total factor productivity measures the technology advancement, the influence of factors such as economies of scale for enterprise production efficiency, according to the production of special mode of operation, its own production and operation efficiency affect the bank's ability to convert savings into loans, and thus to a great extent, determines the bank money creation ability (zhang jianhua, Paul peng wang, 2010 [12]). At the same time, due to information distortion in real enterprises and overestimation of financial risks, most profit-oriented

Banks will stay away from the "low return" and "high risk" real economy and invest in the virtual economy with high return when the risk level is high (Wang Zhuquan et al., 2019[13]). Thus, a bank's risk level determines the proportion of its loanable funds allocated to real economy enterprises. Therefore, this paper will next study the effect mechanism of fintech on Banks' support for the real economy from two channels, total factor productivity and capital risk of Banks.

### 4.2.1 Bank total factor productivity channel

As can be seen from table 5 (1) and (2), there is a significant inverted U-shaped relationship between fintech index and total factor productivity of Banks, indicating that the level of fintech in the early stage can significantly improve the production efficiency of Banks, while the level of fintech in the later stage will reduce the production efficiency of banks. Possible reasons for the early stage of the financial technology such as large data, such as block chain technology improves the ability of banks to obtain information, reduce the degree of information asymmetry between banks and loan enterprises, in the full information and under the premise of reasonable control credit risk, banks may be more deposits into loans to the high level of credit enterprises (Allen N et al., 2010 [14]). However, the late financial technology innovation may have a negative effect of too high investment in research and development, which will not play a big role in the improvement of total factor productivity of banks.

### 4.2.2 Bank capital risk channels

It can be seen from the columns (3) and (4) of Table 5 that the risk of fintech index and bank presents the same inverted U-shaped relationship as the production efficiency of bank. The possible reasons are as follows: the advance of financial technology will increase the risk level of Banks. On the one hand, the realization of fintech requires a high investment cost in the long term, while the excessive investment in technology research and development in the short term may lead to the decline of the profitability of Banks and the increase of operational risks. On the other hand, as the overall technology of the market improves, the competition among Banks intensifies, and Banks are forced to expand their business scope, which may lead to increased risks for some Banks (Costas and Paulo, 2008[15]). In the case of increased risk, Banks may choose to invest lendable funds in the highly uncertain and speculative virtual economy in order to obtain more funds with high liquidity and high return rate. The later financial technological progress will lead to the improvement of the overall competitiveness of the banking industry, thus increasing the risk bearing level of the whole industry.

Table 5 Analysis of the transmission path of fintech in real economy

| | (1) TFPCH | (2) TFPCH | (3)Risk | (4) Risk |
|---|---|---|---|---|
| Fintech | $0.023^{**}$<br>(0.011) | $0.059^{***}$<br>(0.023) | $9.501^{***}$<br>(1.592) | $15.042^{***}$<br>(3.159) |
| $Fintech^2$ | | $-0.009^{*}$<br>(0.005) | | $-1.638^{**}$<br>(0.807) |
| CPI | -0.066<br>(0.075) | -0.067<br>(0.075) | -2.339<br>(1.647) | -2.352<br>(1.644) |
| GDPr | $-0.124^{*}$<br>(0.075) | $-0.126^{*}$<br>(0.075) | -1.002<br>(2.772) | -0.931<br>(2.768) |
| IPO | 0.031<br>(0.036) | 0.025<br>(0.036) | $67.556^{***}$<br>(3.863) | $64.495^{***}$<br>(4.141) |
| Policy | -0.483<br>(0.429) | -0.487<br>(0.428) | 5.939<br>(5.025) | 6.787<br>(5.034) |
| Costinc | $-0.672^{***}$<br>(0.074) | $-0.686^{***}$<br>(0.074) | $-26.501^{**}$<br>(10.581) | $-28.068^{***}$<br>(10.592) |
| ROA | $-14.435^{***}$<br>(3.673) | $-14.964^{***}$<br>(3.679) | $-987.077^{**}$<br>(484.640) | $-1031.376^{**}$<br>(160.833) |
| Year | Fixed | Fixed | Fixed | Fixed |
| Unity | Fixed | Fixed | Fixed | Fixed |
| N | 935 | 935 | 935 | 935 |
| $R^2$ | 0.040 | 0.038 | 0.419 | 0.422 |

### 4.3 Heterogeneity analysis

As the operation and decision-making of state-owned banks are affected by more policy factors and macroeconomic development objectives, it is generally believed in academic circles that the ownership structure of Banks may have an impact on their operating efficiency and risk bearing level (Forssbaeck, 2011[16]; Berger, 2015[17]). Therefore, the nature of bank ownership may ultimately influence the financial resources it provides to the real economy through its influence on the above two channels. Therefore, this paper analyzes the heterogeneity of the above tests in view of the ownership nature of Banks.

It can be seen from Table 6 (1) and (4) that fintech can significantly increase the loan scale of state-owned Banks to the real economy, while it will not have a significant impact on non-state-owned Banks. Columns (2) and (5) describe the impact of fintech on the TOTAL factor productivity of Banks with different ownership. The results show that fintech can significantly improve the total factor productivity of state-owned Banks and non-state-owned Banks, but more for state-owned Banks. The possible reason is that state-owned Banks have stable operation and can make better use of technological innovation to improve their money creation ability. Columns (3) and (6) describe the impact of fintech on the risk of Banks of different ownership. The results show that fintech has a significant negative impact on the risk of state-owned Banks, while it can have a significant positive impact on non-state-owned Banks, that is, fintech increases the risk of state-owned Banks, but reduces the risk of non-state-owned Banks. Possible reasons for the state-owned Banks generally larger scale, financial science and technology development level is higher, relative to the non-state bank has a comparative advantage, technological innovation to improve its relative competitiveness, and the non-state-owned Banks in a relatively backward scientific and technological level for its financial stage, not competitive enough, because the technology to reduce its profitability at the same time, improve the risk management.

Table 6 Heterogeneity analysis of fintech action pathways

| | State-owned Banks | | | Non-state-owned Banks | | |
|---|---|---|---|---|---|---|
| | TFPCH | Risk | RED | TFPCH | Risk | RED |
| Fintech | 0.027** (0.012) | -4.622* (2.639) | 0.359** (0.169) | 0.025** (0.012) | 12.158*** (1.551) | -27.470 (36.184) |
| CPI | 0.045 (0.068) | 0.531 (2.966) | 0.457 (0.954) | -0.030 (0.084) | -2.553 (1.584) | -21.942 (260.655) |
| GDPr | 0.319 (0.096) | -5.523 (5.258) | -0.179 (1.342) | -0.092 (0.008) | -0.129 (2.665) | -42.383 (248.042) |
| IPO | -1.777*** (0.094) | 3.134 (14.961) | 2.072 (1.342) | 0.045 (0.036) | 84.879*** (3.909) | 23.957 (111.929) |
| Policy | 0.039 (0.449) | 4.503 (10.599) | 4.371 (6.283) | -0.273 (0.474) | 6.593 (4.801) | -249.755 (1468.652) |
| Costinc | -2.958*** (0.119) | 13.911 (25.295) | 3.270* (1.665) | -0.615*** (0.074) | -26.899*** (10.088) | 74.431 (230.301) |
| ROA | -150.427*** (20.678) | -6010.274*** (1707.553) | -398.337 (289.061) | -12.598*** (3.628) | -499.892 (459.302) | 30091.5*** (11232.600) |
| Year | Fixed | Fixed | Fixed | Fixed | Fixed | Fixed |
| Unity | Fixed | Fixed | Fixed | Fixed | Fixed | Fixed |
| N | 49 | 49 | 49 | 886 | 886 | 886 |
| $R^2$ | 0.317 | 0.585 | 0.038 | 0.003 | 0.517 | 0.019 |

To sum up, for Banks with different ownership properties, fintech has different influences on their total loans to the real economy and plays corresponding roles through different mechanisms. Financial technology can enhance the total factor productivity and reduce the risk of state-owned Banks to increase their support for the real economy, while for the state-owned Banks, financial science and technology on the one hand, to improve the production efficiency, small amplitude and improve the bank's risk, on the other hand, resulting in its lending to the real economy is not significantly improved.

### 4.4 Robustness test

In order to improve the reliability of the empirical results, this paper change the financial index change of science and technology to inclusive financial index, the level of risk indicators capital assets ratio change to risk assets ratio and the method of building the total factor productivity to the SFA method based on parameter computation, and then perform robustness inspection. The robustness test results show that the test results of changing the measurement index and index construction method have no serious impact on the research conclusions of this paper, so the conclusions of this paper are relatively robust.

## 5. Conclusions

In this paper, a fintech index was established by text mining method and the influence of financial technology innovation on the strength of Banks' support for the real economy was studied with Banks as the function channel. On this basis, the two action mechanisms of bank factor productivity and bank risk were studied through the deA-Malmquist index established. Based on the empirical results, the following conclusions can be drawn: First, for China at present, fintech innovation will not have a significant impact on the balance of loans provided by Banks to real economy enterprises. Second, fintech can influence Banks' support for the real economy through both total factor productivity and risk level. On the one hand, the development of fintech in the early stage can improve Banks' total factor productivity and increase their loanable capital scale. On the other hand, it will increase Banks' risk and reduce their willingness to support the real economy. The later development of fintech will have a negative impact on both. As a result, fintech did not play a significant role in the total amount of loans obtained by the real economy. Finally, the heterogeneity analysis shows that fintech has different mechanisms for the total loans of different ownership Banks to the real economy, leading to different final effects. Fintech can improve the total factor productivity of state-owned Banks, reduce operational risks and increase their loan balance to the real economy. However, for non-state-owned Banks, fintech has an impact on both production efficiency and risk improvement, leading to the failure of its support for the real economy.

The empirical test results of this paper have certain reference significance for the further development direction of fintech and how it can promote the real economy. First of all, Banks should pay attention to the different influences of different stages of fintech development. In the early stage of fintech development, Banks should fully consider their costs and input returns to reduce the risk level. In the later stage, it is necessary to give full play to the ability of fintech to promote money creation and use technological innovation to improve operational efficiency. Secondly, the development of fintech may have a crowding out effect on some banking businesses, leading to a decline in the competitiveness of some small and medium-sized Banks and an increase in their risk level. Relevant departments shall strengthen supervision over such Banks and improve their risk bearing level. Finally, large state-owned Banks should give full play to their market-oriented role, drive non-state-owned Banks to jointly use fintech to enhance their support for the real economy, and realize the effective allocation of financial resources.

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