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Original Paper

Financial Technology Level and Credit Structure Adjustment of Commercial Banks

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Abstract

Under the traditional bank credit model, due to financial control and risk considerations, the growth of credit scale is limited. Banks often adopt short-term credit strategies and tend to issue guaranteed loans instead of credit loans. In recent years, the development of financial technology in commercial banks has broken the credit resource allocation model of the traditional financial system to a certain extent, which is of great significance for optimizing the credit structure of commercial banks. This paper first analyzes the potential transmission pathways through which financial technology may influence commercial banks, and then selects the panel data of 91 commercial banks in China from 2017 to 2021, uses NLP (Natural Language Processing) to construct indicators to measure the level of bank financial technology. Taking commercial banks as the research object, this paper empirically studies the impact of financial technology on the credit structure of commercial banks in China and analyzes the relevant mechanisms. The study found that the development of financial technology of commercial banks can reduce the bank's non-performing loan ratio, promote the optimization of bank credit structure, increase the loan scale and proportion of credit loans, personal loans, medium and long-term loans. For large commercial banks and small and medium-sized banks, There is a significant difference in the degree of optimization of the credit structure. Also, the Optimization of credit structure has brought more customers into the loan business, which has promoted the continuous improvement of the bank's profitability.

Keywords

Financial technology, Commercial bank, Credit structure

1. Introduction

In recent years, with the continuous advancement of technological changes such as big data, artificial intelligence, blockchain, and cloud computing, new financial business models centered on Internet finance and financial technology have emerged, enabling precise matching of financial resources. Fintech uses the new information technology in payment, financing, investment, insurance and other fields to promote financial innovation. The "Financial Technology Development Plan (2022-2025)" issued by the central bank clearly stated that my Chines financial technology should be promoted from "pillars and beams" to a new stage of "accumulation and momentum". Financial technology can not only effectively support the real economy and empower inclusive finance, but also provide strong support for building a modern financial system that adapts to the development of the digital economy.

Due to the widespread information asymmetry between banks and customers in the traditional financial system, the credit supply and demand between banks and customers cannot be balanced through the interest rate mechanism. In the case of limited bank information screening capabilities, the safety and profitability requirements of bank loans make banks try to avoid issuing long-term loans with a high probability of default, replace credit loans with mortgage loans, and often ignore retail financial services, resulting in twisted bank credit allocation. The specific performance is: commercial banks follow the "80-20 rule", firmly believe that 20% of customers can create 80% of profits (Xu et al., 2021), and are unwilling to issue loans to small, medium and micro enterprises and individual customers. At the same time, the loans issued by banks are mainly short-term loans, which also makes "short-term debt and long-term use" the norm in the financing structure of enterprises, which intensifies the risk of corporate leverage and may form systemic financial risks. This also reflects the inability of China traditional financial system to serve the real economy (Zhong et al., 2016; Tang & Xie, 2022). Under the influence of interest rate liberalization, financial disintermediation, and consumption upgrades, commercial banks have begun to gradually realize the importance of "long-tail customers", that is, ordinary bank customers, and the application of financial technology has helped banks alleviate many constraints brought about by the fragmented market structure and asymmetry information.

Under the economic dual cycle pattern, China commercial banking financial system is supposed to pay more attention to inclusive finance, put more emphasis on serving small and medium-sized enterprises, and serve a wider range of "long-tail customers" (Ba, 2020). Therefore, as the main supplier of funds in the economic system, it is of great significance for the banking industry to use financial technology to innovate, adjust and optimize the allocation of credit resources. The development of financial technology in commercial banks has provided a new idea for optimizing the credit structure adjustment of commercial banks. Therefore, exploring the specific relationship between the level of financial technology of commercial banks and the optimization of credit structure from an empirical point of view, and clarifying the transmission process and mechanism of action between the two, will upgrade the current commercial bank credit model, promote inclusive finance and play an important role in promoting the development of the real economy.

The second part below will conduct a literature review; the third part will put forward reasonable hypotheses on the optimization of bank credit structure and its mechanism based on theoretical analysis; the fourth part will introduce the research design and give a specific model; In the fifth and sixth parts, the empirical results and robustness tests will be analyzed separately; the seventh part will analyze the heterogeneity; the eighth part will further analyze the research in this paper; the ninth part will give conclusions and policy recommendations based on the results of the empirical research.

2. Literature Review

Aiming at the causes of unreasonable credit allocation strategies of commercial banks under the traditional financial model, existing research mainly focuses on three aspects: macro monetary policy uncertainty, micro bank risk aversion, and single retail financial business. At the macro level, due to the imperfection of the financial market and the instability of monetary policy, when the uncertainty of monetary policy rises, banks tend to reduce the scale of lending, shorten the term of lending, narrow the scope of lending, and increase loan approval standards and interest rates. As a result, the financing costs of small enterprises and individuals have been increased (He et al., 2020; Lian et al., 2022; Song et al., 2019). In terms of bank risk avoidance, banks mainly collect relevant information disclosed by companies manually and rate corporate credit based on simple scoring models. This is not only subjective, but the information is usually not time-sensitive. For example, compared with state-owned enterprises, small enterprises have less market attention, poor disclosure quality, and suffer from obvious information asymmetry between banks and enterprises. Therefore, in order to avoid risks, banks generally increase the collateral requirements for mortgage loans, and are more inclined to lend to state-owned enterprises with "implicit guarantees" (Lin & Li, 2001). In terms of retail financial business, the design, promotion and sales of financial retail products are still relatively simple, there is a lack of unified planning and coordination among various products, and the phenomenon of homogeneity is obvious (An et al., 2019), and the retail business still uses physical outlets as the main channel, the channels for consumption and life scenarios are relatively limited, and customer stickiness is weak (Li, 2018), and the needs of long-tail customers in the retail business are often not met.

The empowerment of financial technology can use information technology to make up for the shortcomings of traditional bank business models, and have a profound impact on the total factor productivity, profitability, risk-taking level, asset or liability structure, and industry competition pattern of commercial banks (Shen & Guo, 2015; Liu, 2016; Qiu et al., 2018; Meng et al., 2020; Yu et al., 2020). Therefore, most scholars believe that the development of financial technology in banks has a positive impact on their operations. First of all, in terms of bank operations, the application of fintech can extremely compress the space-time distance between banks and customers, expand business to the greatest extent, and at the same time diversify business, customer channel and product innovation, optimize customer experience (Huang & Huang, 2018), help banks to search for customers more accurately and efficiently, provide convenient services (Pan & Qu, 2018), and enhance the ability of banks to acquire customers. Secondly, in terms of profitability, the application of financial technology can fully integrate financial resources, accelerate the development of intermediary business and other channels to improve bank operating performance (He & Liu, 2019). Finally, in terms of risk control, the Internet and big data technology can collect more dimensional customer information for commercial banks and draw a more objective and complete customer portrait, thereby alleviating the information asymmetry problem caused by structural credit shortage and strengthening the bank's The ability to resist and manage risks (Liu & Jiang, 2020).

Existing literature mainly distinguishes fintech from two aspects: external financial technology and internal financial technology (Cheng & Qu, 2020). Most scholars focus on digital financial and adopt the China digital financial index constructed by Guo et al. (2020), from the perspectives of "width", "depth" and "degree of digitalization" of financial technology development, it studies the specific impact of the improvement of external financial technology level on commercial banks' business performance, competition model, and risk-taking. Some studies have shown that the development of external financial technology affects the risk preference of the asset side by affecting the structure of the bank's liability side (Qiu et al., 2018). The development of financial technology will also intensify the competition of commercial banks through the two channels "market crowding out" and "technology spillover" (Su et al., 2020). In terms of the external effects of the level of external financial technology, existing research clearly points out that the promotion of external financial technology can reduce the financing cost of enterprises, promote corporate innovation, and help the process of "deleveraging" in the corporate sector (Tang et al., 2020; Li et al., 2020). The research of these literatures on the level of financial technology only stays at the level of regions and industries. In order to further study the influence mechanism of the internal financial technology level of banks, a few scholars have built their own financial technology indicators at the bank level to study the impact on the bank itself and external companies by the improvement of the internal financial technology level of banks. Jin et al. (2020) found that the application of banking financial technology has reduced the information asymmetry between banks and enterprises, and the risk-taking level of large banks has been significantly reduced and has a "crowding out effect" on small and medium-sized banks. Zhang et al. (2022) found that the use of financial technology at the bank level can affect the "deleveraging" of private enterprises. Li et al. (2022) pointed out that the development of financial technology within banks can alleviate the phenomenon of "short-term debt and long-term use" of enterprises. However, few scholars have paid attention to the mechanism of the bank’s financial technology level on the optimization of the bank’s credit structure. Only Xu et al. (2021) found that the improvement of the bank’s financial technology level can expand the credit scale and promote the credit structure adjustment of the loan business.

According to the existing literature, the research on the reasons for the unreasonable credit allocation strategy has been relatively mature, and most scholars put forward suggestions for optimizing the credit allocation strategy from different angles under the framework of traditional finance. At the same time, academic research on financial technology empowering commercial banks is mainly based on the development of external financial technology, and studies the impact on traditional commercial bank financial models from the perspective of regional inclusive finance. A small number of scholars use their self-constructed financial technology indicators as proxy variables of bank financial technology to study the economic benefits and transmission mechanisms of the development of the financial technology, but they only stay in the banking industry competition, risk-taking, business performance and other aspects. However, there is a lack of research on the impact of the development of bank financial technology on the optimization of bank credit structure. Compared with the traditional means of optimizing credit structure, banks are more likely to fundamentally solve problems such as "information solitary islands", "humdrum service" and "financing discrimination" through the development of financial technology, optimize the allocation of credit resources, and promote the development of the real economy. In order to fill the gap in the academic research area, this paper examines the relationship between the level of financial technology and the adjustment of bank credit structure from the perspective of banks, and on this basis, this paper examines whether bank financial technology can have a positive effect on business performance through optimizing credit structure.

The marginal contribution of this paper is mainly reflected in the following aspects: First, starting from the optimization of bank credit structure, it expands the influence of bank financial technology level on itself to the level of credit structure, and further examines the economic benefits brought by financial technology to banks. The benefits are a strong proof that banking financial technology can break through the traditional financial model, optimize the credit structure, and empower the real economy. Second, this paper provides a new idea for optimizing the allocation of credit resources, using information technology to fundamentally solve a series of problems caused by information asymmetry between banks and customers. Third, this paper proposes and examines the role of bank financial technology in optimizing the credit structure from multiple dimensions, which provides a clear direction for commercial banks to strengthen financial technology and also provides strong support for clarifying the relationship between banks and enterprises. Fourth, this paper use the self-constructed financial technology dictionary to construct bank financial technology indicators, and introduce text sentiment analysis to identify the positive and negative tendencies of news, so as to avoid overestimating the level of bank financial technology.

3. Theoretical Analysis and Research Hypothesis

3.1 Traditional Bank Credit Model and Credit Structure Distortion

In the financial market dominated by banks, bank loans are the main way of external financing for enterprises and individuals. Under the traditional bank credit model, the information asymmetry between banks and customers is mainly reflected in two aspects of "information collection" and "data analysis". And other issues, to some extent, also inhibit the development of retail financial business. In recent years, commercial banks have begun to deploy fintech by setting up fintech subsidiaries or cooperating with existing fintech companies. The underlying technologies centered on financial cloud, big data control, and blockchain encryption have fundamentally changed the traditional business model, provided banks with powerful computing power, accurately portrayed customer groups, and accelerate the bank's growth, digital transformation and upgrade. Front-end application platforms such as "precision marketing" and "smart housekeeper" are also building bridges for banks and enterprises to transmit information under different business scenarios. Therefore, the application of banking financial technology can significantly mitigate the information asymmetry between banks and customers at the credit level, improve the operating efficiency of banks, improve service quality, provide diversified services, and reduce the non-performing loan ratio of banks (Li et al., 2022). Based on these thesis, this paper proposes the following hypotheses:

H1: The improvement of financial technology level of commercial banks can promote banks to expand their loan scale.

H2: The improvement of financial technology level of commercial banks can promote the adjustment of term structure.

H3: The improvement of financial technology level of commercial banks can promote the adjustment of credit structure.

H4: The improvement of financial technology level of commercial banks can promote the adjustment of customer structure.

(2) Transmission mechanism between financial technology and the optimization of credit structure

Improvement of information screening capabilities of commercial banks. In terms of data collection, banks use financial technology to promote their own soft information collection capabilities (Jin et al., 2020). Specifically, big data technology can realize continuous monitoring of customer information and real-time capture and summary of data through data mining. While providing banks with multi-dimensional high-quality information, it also reduces the marginal cost of information collection. In terms of data analysis, artificial intelligence technology can automatically fit the data according to the existing model and mine the nonlinear relationship in the data. The improvement of information screening ability shortens the identification and certification time of customers, and helps banks identify potential high-quality customers.

The improvement of the risk control level of commercial banks. In terms of risk control, financial technology has, to a certain extent promoted the transformation of the bank lending model from mortgage loans to credit loans, thereby promoting bank credit resources to favor unsecured and unsecured private enterprises with good credit. For example, the bank credit department can make full use of the "traceable", "encrypted", and "unforgeable" characteristics of blockchain technology to realize real-time supervision of funds and risk warning. At this stage, the new commercial bank risk control model mainly includes big data risk control model and digital supply chain financial model. The big data risk control model based on the big technology ecosystem includes tens of thousands of "digital footprints" of enterprises into the scope of investigation, detect the company's operating flow and other financial conditions to reduce the cost of risk control. The use of such technologies by banks can lower the financing threshold for enterprises lacking historical information (Huang & Qiu, 2021 Management World), and optimize corporate leverage while improving financial inclusion. The digital financial model based on blockchain and supply finance integrates enterprises on the same chain. Enterprises in the supply chain register their information based on the blockchain technology platform. The high degree of synergy between enterprises guarantee the accuracy of information. Banks use this platform to collect, analyze, manage, and verify data, this platform provide new ideas for preventing information manipulation, malicious fraud, and other behaviors. thereby alleviating "financing discrimination" against companies. Based on these thesis, this paper proposes the following hypotheses:

H5: The development of financial technology in commercial banks can improve information identification capabilities and risk management level, reduce risk taking, and thus optimize credit structure. The transmission mechanism is shown in Figure 1.

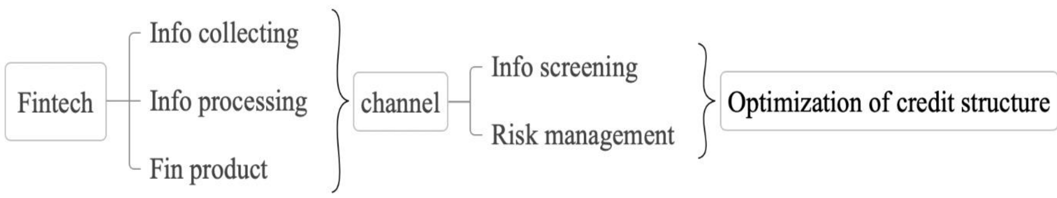

Figure 1. The Transmission Mechanism of Financial Technology

4. Research Design

4.1 Sample Selection and Data Sources

Considering that 2017 is usually regarded as the "first year of financial technology" in the literatures (Lu & Ma, 2021), on the premise of data availability, this paper sets 2017 as the starting year of sample data, the research objects of this paper include state-owned commercial banks, joint-stock commercial banks, city commercial banks, rural commercial banks, village banks and private banks. The data at the bank level comes from the Bankfocus (Bankscope) database and the Wind database. This paper fills missing values by manually querying the annual reports of commercial banks. The bank financial technology index in this paper at the individual level of Chinese commercial banks is constructed by ourselves, and the macroeconomic data comes from the Qianzhan database.

4.2 Variable Selection

4.2.1 Interpreted Variables:

Credit expansion (Loan_g)

The application of cutting-edge financial technology can help commercial banks establish a more comprehensive customer portrait, and help banks achieve precise marketing, provide customers with diversified financial services, and meet the needs of customers while alleviating information asymmetry. The specific performance is that the continuous growth of personal loans and credit loans in recent years has promoted the further adjustment of the credit structure. This paper uses the bank loan growth rate (Loan_g) as a proxy variable for credit expansion.

Loan credit structure adjustment (Cred_pro) (Credit_g)

This paper uses the proportion of bank credit loans to total loans (Cred_pro) and credit loan growth rate (Credit_g) as proxy variables for credit structure adjustment. And this paper select the proportion of secured loans (_pro) and the growth rate of secured loans (_g) to compare with (Cred_pro), where secured loans include guaranteed, mortgage and pledged loans (He, 2016).

Loan customer structure adjustment (Per_p) (Per_g)

Zhao et al. (2019) pointed out that the proportion of retail business or corporate business to total business can be a good measure of the degree of bank retail transformation. This paper adopts a similar approach, taking the proportion of bank annual personal loans to total loans and the growth rate of personal loans as proxy variables for the structural adjustment of customers. And selecting the proportion of corporate loans (Cor_pro) and corporate loan growth rate (Cor_g) to compare with.

Adjustment of loan term structure (Ml_p) (Ml_g)

In this paper, the proportion of the bank's annual medium-term and long-term loans to the total loan and the growth rate of medium-term and long-term loans (Ml_g) are used as proxy variables for the adjustment of the bank's loan term structure.

Core Explanatory Variables:

Bank financial technology level (Fin)

In the existing literature, the level of financial technology is mainly measured from the external and internal (bank) levels. Among the many external financial technology indicators, the Peking University Digital Inclusive Finance Index compiled by Guo et al. (2016) is widely used by scholars. At the same time, some scholars use python to obtain the frequency of financial technology-related words that appear in the news or annual report to construct external financial technology indicators. Su et al. (2020) constructed regional external financial technology indicators through text mining and Internet financial vocabulary related to digital payments, Internet loans, and Internet wealth management. For the construction of financial technology indicators at the bank level, Jin et al. (2020) focused on the four major areas in which financial technology empowers commercial bank credit and the core technologies they rely on, in order to improve the measurement accuracy, selected keywords and applied factor analysis to construct index. Li et al. (2022) conducted text mining on patent application documents of each year through a self-built financial technology dictionary, and used the statistically obtained number of bank financial technology patent applications as a proxy variable. In this paper, referring to the above literature, the following steps are executed to construct the financial technology indicators of commercial banks:

Firstly, Constructing the bank fintech lexicon. This paper adopts two different classification methods for banking fintech. The first category is to divide fintech activities into payment and settlement, deposit and loan, capital raising, investment management, and market facilities according to the classification standards of the Basel Committee on Banking Supervision (BCBS). Since this essay focuses on credit issues, the payment and settlement function is not considered for this time. According to the above taxonomy and the relevant subject vocabulary in the "Fintech Development Plan (2022-2025)" (hereinafter referred to as "Plan") issued by the central bank, the fintech lexicon constructed is shown in Table 1. The second type of classification divides fintech into underlying technology and fintech applications. The fintech lexicon constructed in this paper based on the vocabulary related to "underlying technology" and "application" in the Plan is shown in Table 2.

Table 1. Thesaurus Based on the Division of Financial Technology Business Fields

Deposits & Loans & Capital Raising	Investment Management	Market Facilities
Credit Precipitation	Predictive Model	Open Banking
Precision Marketing	Scoring Modeling	Inclusive Finance
Loan Settlement	Data Analysis	Distributed Account
Accurate Rating	Online Banking	Net Union
Investment-loan Linkage	Cyber Insurance	Fusion Architecture
User Portrait	Robo-advisor	Internet of things
Mobile Banking	Anti-fraud Model	Mobile Internet
Scenario Finance	Electronic Transaction	Stream Computing
Loan Platform	Quantitative Finance	Biometrics
Personalized Pricing		Data Analysis
Equity Crowdfunding		Billion-level Concurrency
Cloud Computing		Authentication
Credit Factory		
Blockchain		
Direct Banking		
Big Data		

Secondly, Crawling financial technology-related texts of commercial banks. This paper matches the bank name with the keywords of financial technology, and obtains the news text of each bank for each year through python crawlers. In order to improve the credibility of the news text, this paper adopts the following methods to re-screen the text after the primary screening: 1. Reduce duplication of the text; 2. Keep the text where bank name and keywords emerge in the news title; 3. Keep text in which no keyword appears in the news title but appears more than a certain number of times in the main body.

Thirdly, Text sentiment analysis. In order to avoid overestimating financial technology index, the sentiment analysis technology of python is applied to calculate the emotional tendency of news by constructing a Chinese financial sentiment dictionary, then the obtained news texts are divided into two categories: positive news and negative news. Using factor analysis to weight positive news to build fintech indicator.

Finally, Index standardization. Considering that large-scale banks have more news reports than small and medium-sized banks, this paper divides the financial technology indicators of each bank by the total number of annual news of the bank, and then performs logarithmic transformation to obtain a standardized index.

Controlled Variables

This paper controls variables at the bank level and the macro level. The bank level includes the bank type (Bank_type), the value is 1 for small and medium-sized banks, and the value is 0 for large banks. Bank size (Bank_size), represented by the total assets of commercial bank. Net interest margin (Bank_nim), represented by dividing net interest income by the average balance of interest-earning assets. Growth capacity (Bank_grow), represented by the growth rate of asset scale. Profitability (Bank_roe), expressed by return on equity, measures the bank's capital utilization efficiency. Operating efficiency (Bank_cir), measures the bank's operating efficiency by the cost-to-income ratio, that is, dividing total costs by operating income. Liquidity (Bank_liq), measures the liquidity status of a bank by the ratio of current assets to total assets. Capital structure (Bank_str), represented by the ratio of equity assets to total assets. At the macro level, this paper controls the level of economic development (GDP_g), expressed as GDP growth rate. The level of inflation (CPI), expressed as the consumer price index. Monetary policy environment (M2_g), expressed as growth rate of broad money.

Table 2. Main Variables and Variable Meanings

	(1) Variable Name	(2) Variable Symbol	(3) Variable Meaning
Explained Variable			
1	Credit Expansion	Loan_g	Loan growth rate
2	Term Structure	Ml_p Ml_g	Proportion and growth rate of medium and long-term loans
3	Credit Ctructure	Cred _pro Credit_g	Proportion and growth rate of credit loans
4	Customer Ctructure	Per_p Per_g	Proportion and growth rate of personal loans
Core Explanatory Variable			
5	Bank Fintech Level	Fin	Bank FinTech Level Index
Control Variable			
6	Bank Type	Bank_type	1 for small and medium banks, 0 for large banks
7	Bank Size	Bank_size	
8	bank size	Bank_size	Total assets
9	Net Interest Margin	Bank_nim	Net Interest Income/average balance of interest-earning assets
10	Growth Ability	Bank_grow	Asset growth rate
11	Profitability	Bank_roe	Roe

12	Operating Efficiency	Bank_cir	Cost/Operating Income
13	Fluidity	Bank_liq	Current Assets/Total Assets
14	Capital Structure	Bank_str	Equity Assets/Total Assets
15	Economic Level	GDP_g	GDP growth rate
16	Inflation Level	CPI	Consumer Price Index
17	Monetary Policy	M2_g	Broad money growth rate

4.3 Model Setting

In this paper, the following two-way fixed effect model is used to verify and analyze the relationship between the bank's financial technology level and credit structure adjustment. The formula (1) is as follows:

$$loan_{i,t} = \alpha + \beta_0 fin_{i,t} + \lambda_0 control_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

In model (1), i represents the bank, t represents the year, and the explained variable Loan represents the credit loan structure of the bank, including indicators of loan scale, term structure, credit structure, and customer structure. The core explanatory variable Fin represents an index constructed by text crawlers to measure the level of financial technology at the bank level. Control represent the control variable vectors of the model, including bank-level and macro-level control variables. ηi and μt respectively represent the fixed effect of individual level and the fixed effect of time level. εi,t-1 is the random disturbance item of the model. Considering that the disturbance items of the same bank in different years usually have autocorrelation, this paper uses cluster robust standard errors.

4.4 Descriptive Statistics

Table 3. Variable Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)
Variable Symbol	Number of Observations	Average	Standard Deviation	Minimum	Maximum
loans	455	1.217e+06	3.172e+06	10,535	2.067e+07
loans_increase	455	133,767	305,134	-131,763	2.043e+06
loan_g	455	0.202	0.110	-0.229	0.775
_pro	455	0.709	0.123	0.100	0.990
_g	455	0.198	0.489	-0.436	1.18
cor_pro	455	0.592	0.246	0.423	0.721
cor_g	455	0.171	0.185	-0.464	0.777
bank_size	455	2.225e+06	5.546e+06	37,347	3.517e+07
bank_grow	455	0.120	0.0889	-0.164	0.436
bank_roe	455	0.0963	0.0383	0.00700	0.248

bank_cir	455	0.347	0.0790	0.200	0.613
bank_liq	455	0.209	0.0784	0.00630	0.496
bank_str	455	0.0762	0.0112	0.0464	0.119
bank_type	455	0.868	0.339	0	1
gdp_g	455	0.0600	0.0197	0.0230	0.0810
cpi	455	102	0.699	100.9	102.9
m2_g	455	0.0860	0.0100	0.0700	0.100
fin	455	0.343	0.771	0	4.838
cred_pro	455	0.191	0.123	0.0131	0.798
credit_g	455	0.355	0.363	-0.315	0.857
per_p	455	0.311	0.132	0.000900	0.736
per_g	455	0.323	0.380	-0.185	1.029
ml_p	455	0.524	0.331	0	0.799
ml_g	455	0.260	0.368	-0.462	1.175
total number of banks	91	91	91	91	91

Table 3 reports the descriptive statistics of the variables in this paper. It can be seen that the average proportion of personal loans, credit loans and medium-term and long-term loans are 31.3%, 19.1% and 52.4% respectively, and the average proportions of corporate loans and guaranteed loans are 59.2% and 70.9% respectively. It shows that the current loan business of banks is still dominated by corporate loans and guaranteed loans. The average growth rates of personal loans, credit loans, and medium-term and long-term loans are 32.3%, 35.5%, and 26.0% respectively, which were higher than the growth rates of corporate loans and guaranteed loans of 17.1% and 19.8%. It shows that banks are gradually increasing their allocation on credit loans and personal loans in recent years. However, from the perspective of the maximum and minimum, there are significant differences among different banks.

5. Analysis of Empirical Results

5.1 Hausman Test and Basic Regression

This paper first uses the robust Hausman test to determine whether to use the fixed effect model or the random effect model. The results show that in the regression of each explained variable, the p value is 0.0000, so the null hypothesis is strongly rejected, and the fixed effect model should be used. This paper conducts a regression analysis on formula (1) based on the growth rate of total loans of commercial banks (loan_g). The regression is based on the clustering robust standard error to judge the significance. The results are shown in Table 4. The regression results in column (1) show that under the premise of not controlling the year fixed effect and individual fixed effect, the application of financial technology in commercial banks has a significant positive impact on the growth rate of bank loans. And this effect is significant at the 5% level. Considering that this significance may be caused by the time trend of the sample data. For this reason, this paper further controls the time fixed effect and the individual fixed effect in the robustness test. The results in column (2) show that in the case of considering the fixed effect, the application of financial technology still has a positive impact on the growth rate of bank loans. And it is significant at the 5% level. The regression results confirm the H1 of this paper, indicating that the improvement of the financial technology level of commercial banks can promote banks to expand their loan scale.

In order to further analyze the impact of the application of financial technology in commercial banks on the loan structure. This paper verifies H2, H3, and H4 from the credit structure, customer structure, and term structure of bank loans. The results in Table 5 all control year fixed effects and individual fixed effects. In terms of credit structure, the results in column (1) in Table 5 show that the regression coefficient of financial technology application on the proportion of credit loans (Cred_pro) is positive and significant at the 1% level, indicating that the application of financial technology can significantly promote bank to increase the proportion of credit loans and promote the credit structure adjustment. The results in column (2) show that the regression coefficient of financial technology applications on the growth rate of bank credit loans (Credit_g) is also significantly positive at the 1% level. This shows that after the use of financial technology, the scale of bank credit loans has a tendency to accelerate expansion. On the other hand, considering the robustness of the results, this paper regresses the proportion of guaranteed loans (_pro) and its growth rate (_g). The results in columns (3) and (4) show that the application of financial technology has insignificant impact on (_pro) and (_g). This result also reflects that the application of financial technology has a significant effect on the credit structure. Specifically, based on the above regression results, this paper believes that the effect of the application of financial technology is more on customers who were unable to provide collateral originally, rather than "high-quality" customers who can provide sufficient collateral. In addition, the signs and significance of the controlled variables are logical.

In terms of customer structure, under the premise of controlling the year fixed effect and individual fixed effect, the results in column (1) in Table 6 show that the regression coefficient of fintech applications on the proportion of personal loans (Per_p) is positive, and the regression coefficient is significantly at the 1% level, indicating that the application of financial technology can effectively increase the proportion of personal loans and promote commercial banks to achieve retail transformation. It also shows that the application of financial technology can make up for the bank's original deficiencies in customer acquisition, product design and risk control of retail business to a certain extent, and promote the development of retail business. The results in column (2) show that the regression coefficient of fintech application on personal loan growth rate (Per_g) is significantly positive at the 5% level. This shows that with the continuous improvement of the level of financial technology, the personal loan scale of commercial banks has a trend of accelerated expansion. On the other hand, considering the robustness of the results, this paper regresses the proportion of bank corporate loans (Cor_pro) and its growth rate (Cor_g), and the results of columns (3) and (4) show that financial technology applications have an insignificant impact on corporate loans. This shows that the operation of commercial banks on corporate loans is relatively mature, and the impact of financial technology on it is not obvious. On the other hand, it also reflects that the level of financial technology has adjusted the customer structure. Individual customer groups have more opportunities to obtain bank loans. At the same time, this effect also alleviates "credit discrimination".

In terms of term structure, under the premise of controlling the year fixed effect and individual fixed effect, the results in column (1) in Table 7 show that the application of fintech has a positive effect on the proportion of bank medium-term and long-term loans (Ml_p), and this positive effect is significant at the level of 5%, indicating that the application of financial technology has alleviated the distortion of the term structure caused by the preference of commercial banks for short-term loans, and promoted banks to expand the amount of medium-term and long-term loans. To a certain extent, it can also alleviate the financing pressure of some companies, thereby reducing the moral hazard borne by banks. The results in column (2) show that the regression coefficient of financial technology application on medium-term and long-term loan growth rate (Ml_g) is significantly positive at 1% level. This shows that with the continuous improvement of the level of financial technology, the scale of medium-term and long-term loans of commercial banks has a tendency to accelerate expansion. Based on the above regression results, this paper believes that the use of financial technology by banks can reduce the term premium of long-term loans and the supervision cost of long-term loans, optimize the credit term structure, and meet the long-term financing needs of growing enterprises.

Table 4. Impact of Fintech on Loan Expansion

	(1)	(2)
	Loan_g	Loan_g
fin	0.0296**	0.0288**
	(2.2330)	(2.3288)
_cons	0.6181	1.0375
	(0.8567)	(1.1484)
controlled variable	control	control
fixed effect (year)	no	control
fixed effects (individual)	no	control
N	455	455
r2_a	0.2177	0.2208

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

Table 5. Impact of Fintech on Credit Structure

	(1)	(2)	(3)	(4)
	Cred_pro	Credit_g	_pro	_g
fin	0.1013***	0.3426***	0.0001	0.0981
	(3.2334)	(3.4274)	(0.0057)	(1.3868)
bank_nim	0.3330	-5.2778	0.7003	-3.2014
	(0.4231)	(-1.3783)	(0.8047)	(-0.8973)
bank_grow	-0.0441	-0.1512	0.0378	0.2919
	(-1.0653)	(-0.5918)	(0.8179)	(1.3989)
bank_roe	-0.0815	-1.3612	0.1417	3.5429
	(-0.2945)	(-1.0658)	(0.5569)	(1.3997)
bank_cir	-0.1198	-1.6686**	0.2314*	0.6695
	(-0.7248)	(-2.4733)	(2.2132)	(0.9598)
bank_liq	-0.0253	-0.3936	0.0830	0.0919
	(-0.3921)	(-1.3814)	(1.0257)	(0.5993)
bank_str	-0.1323	-9.4552***	-0.1448	5.0248*
	(-0.3202)	(-3.1306)	(-0.2986)	(1.7515)
gdp_g	0.8653***	5.6570***	-1.0137***	-1.3473
	(3.0637)	(3.3582)	(-4.7890)	(-1.1822)
cpi	-0.0016	-0.0638***	-0.0102	-0.0250
	(-0.2566)	(-2.9983)	(-1.5553)	(-1.0487)
m2_g	3.2897*	24.1383***	-3.2341**	11.5435
	(1.8255)	(3.7983)	(-2.0334)	(1.0206)
_cons	0.0665	6.0536**	2.0744***	0.8794
	(0.1181)	(2.5415)	(3.7599)	(0.6395)
controlled variable	control	control	control	control
fixed effect (year)	control	control	control	control
fixed effects (individual)	control	control	control	control
N	455	455	455	455
r2_a	0.1269	0.3175	0.0811	0.0020

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

Table 6. Impact of Fintech on Customer Structure

	(1)	(2)	(3)	(4)
	Per_p	Per_g	Cor_pro	Cor_g
fin	0.0714***	0.1486**	0.0028	0.0070
	(3.4091)	(2.2604)	(0.1849)	(0.3199)
bank_nim	-0.7280	4.1636	-1.7298	0.7298
	(-0.9105)	(0.8957)	(-1.1138)	(0.2885)
bank_grow	-0.0366	-0.1468	0.0677	0.2341**
	(-1.0514)	(-0.8176)	(0.8641)	(2.0336)
bank_roe	-0.1551	-0.7089	-1.5215	1.9133*
	(-0.9712)	(-0.7265)	(-1.5640)	(1.8493)
bank_cir	-0.2681**	0.4517	0.0937	-0.4685
	(-2.5512)	(0.5764)	(0.4431)	(-1.5341)
bank_liq	-0.0437	1.4247**	0.0996	-0.3031*
	(-0.8184)	(2.3508)	(1.1856)	(-1.9516)
bank_str	-0.0172	11.7490*	-1.9560**	2.0258*
	(-0.0531)	(1.9265)	(-2.0681)	(1.8140)
gdp_g	0.6441**	-2.6497*	-1.6082***	0.1869
	(2.3502)	(-1.7433)	(-2.9972)	(0.1761)
cpi	-0.0009	-0.0350**	-0.0193**	-0.0106
	(-0.2727)	(-1.9931)	(-2.4154)	(-0.9937)
m2_g	3.3990***	-10.5699*	-7.1244***	1.2400
	(2.8287)	(-1.6882)	(-3.3575)	(0.3963)
_cons	0.1972	3.6051*	3.5636***	0.9543
	(0.4710)	(1.7832)	(3.1173)	(0.6875)
controlled variable	control	control	control	control
fixed effect (year)	control	control	control	control
fixed effects (individual)	control	control	control	control
N	455	455	455	455
r2_a	0.2492	0.2138	0.1231	0.0587

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

Table 7. Impact of Fintech on Term Structure

	(1)	(2)
	Ml_p	Ml_g
fin	0.2051**	0.2451***
	(2.1071)	(2.7395)
_cons	1.5298*	2.6969
	(1.7959)	(1.0579)
controlled variable	control	control
fixed effect (year)	control	control
fixed effects (individual)	control	control
N	455	455
r2_a	0.0356	0.0747

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

5.2 Difference-in-Differences Model

In order to further confirm the accuracy of the above benchmark regression results and analyze the effect of financial technology on commercial banks in different years, this paper constructs a DID model to re-examine the impact of financial technology on credit structure, and conducts a parallel trend test. The regression formula (2) is as follows, yeart is a time dummy variable, this paper sets 2017 as the base year, the value of years (2018, 2019, 2020, 2021) after the bank applies financial technology is 1, and the value of 2017 is 0. The coefficient of yeart×finit mainly analyzes the difference in the impact of the financial technology on the credit structure in the experimental period and the base period. The specific results are as follows:

$$loan_{i,t} = \alpha + \beta_0 fin_{i,t} + \delta_0 year_t fin_{i,t} + \lambda_0 control_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

The regression results show that after controlling the individual and time fixed effects at the same time, the impact of bank financial technology on credit structure is still significant. Figure 2, Figure 3, Figure 4, Figure 5, Figure 6, and Figure 7 show the parallel trend test for the proportion of credit loans, credit loan growth rate, the proportion of personal loan, personal loan growth rate, the proportion of medium-term and long-term loan, medium-term and long-term loan growth rate, the vertical axis is the coefficient of the interaction term. It can be seen from the figure that, to a certain extent, it can be considered that the impact of the improvement of the financial technology level in experimental years on credit loans, personal loans, and medium-term and long-term loans is significantly positive, and there are obvious differences. Compared with the base period, this impact tends to increase year by year. This confirms the baseline regression results from another perspective. Therefore, the above regression conclusions are robust.

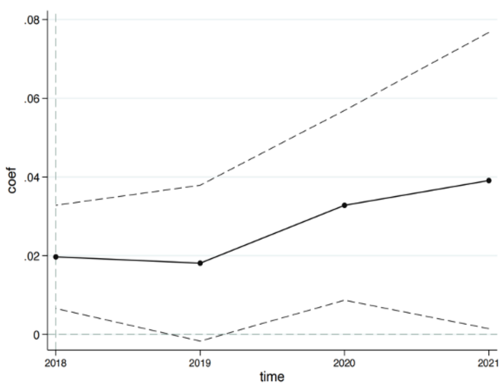

Figure 2. Proportion of Credit Loans

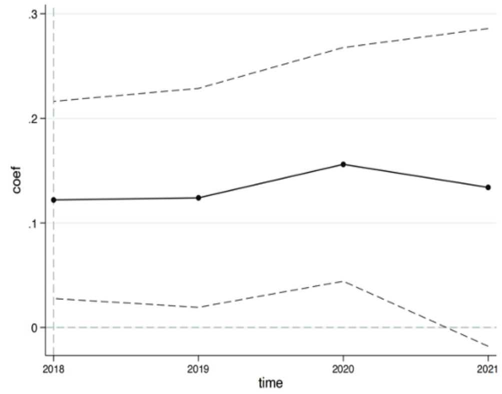

Figure 3. Growth Rate of Credit Loan

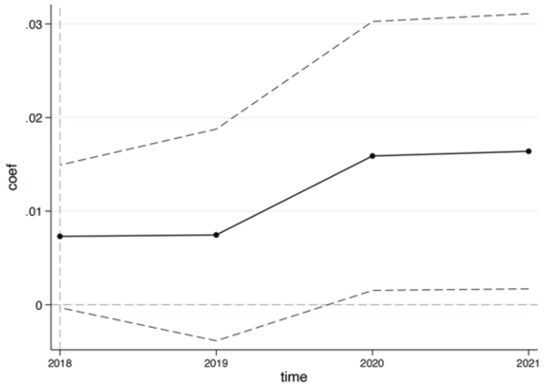

Figure 4. Proportion of Personal Loans

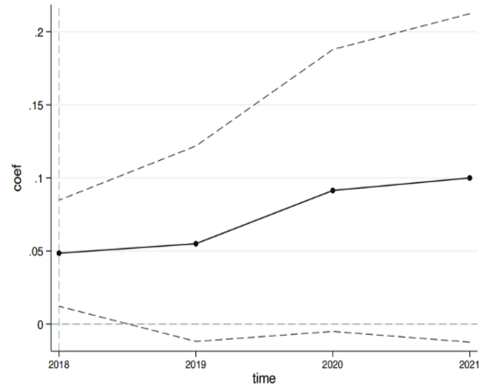

Figure 5. Growth Rate of Personal Loan

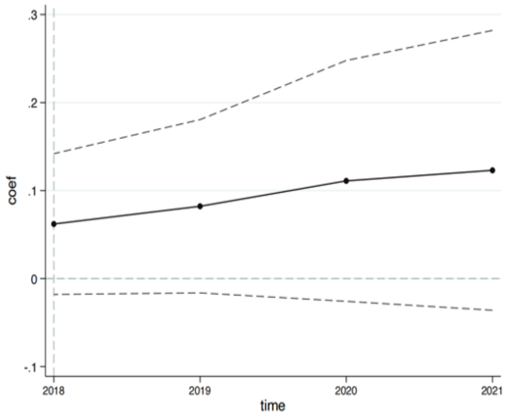

Figure 6. Proportion of ML Loans

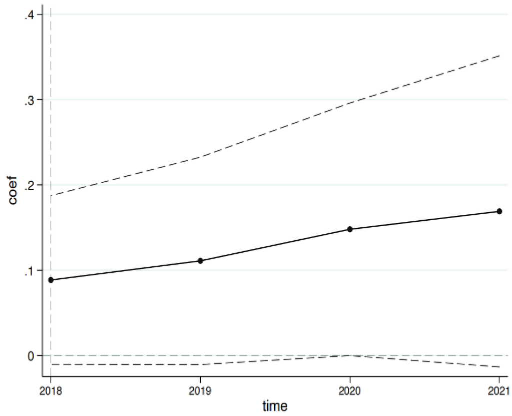

Figure 7. Growth Rate of ML Loans

Robustness Test

The endogenous sources of this essay are mainly manifested in two aspects: one is the omitted variable bias. Although this paper controls a series of variables at the bank level and the macro level, the above estimates may still miss some unobservable factors that affect the level of financial technology at the bank level. The second is the problem of sample selection bias, because some large joint-stock banks have a better credit structure than small banks, city commercial banks, and these large commercial banks may actively manage to improve their financial technology level, which means the above regression results may only reflect correlation rather than causation. Traditional causal analysis often assumes that researchers have controlled the important factors that explain the dependent variable and have not missed important independent variables. However, the data used in research often cannot meet this assumption, or the observed objects are not random, so problems of endogeneity or sample selection bias often occur, resulting in inaccurate and biased causal analysis, or even errors. In this paper, two methods are used to test the robustness of the regression results.

Considering that the core explanatory variable "fin" has a certain lag in construction, this paper advances the bank fintech indicators by two years. The results in Table 8 show that after advancing the application of financial technology by two years, the impact on the proportion and growth rate of credit loans, personal loans, and medium-term and long-term loans is not significant. This is obviously different from the above regression results, and it also confirms that commercial banks have a significant impact on the expansion of credit loans, personal loans, and medium-term and long-term loans through the development of financial technology, and the benchmark regression results are robust.

Large-scale and powerful banks are more likely to develop financial technology, and banks with good credit structure are more likely to use financial technology to further seek better development. In order to avoid endogenous problems caused by reverse causality, this paper takes the lagged one-period item of the explained variable of bank credit structure in the above regression as the explanatory variable, and takes the financial technology level indicator fin as the explained variable. If the regression result is significantly positive, it indicates that banks that perform well in terms of credit structure are more inclined to choose to improve their financial technology level to expand the financial services. If the regression result is not significant, it indicates that the performance of bank credit structure will not have a positive effect on the promotion of financial technology. The results in Table 9 show that the proportion and growth rate of credit loans, personal loans, and medium-term and long-term loans with a lag of one period have no significant impact on the degree of financial technology application, indicating that there is no such reverse causality, and the benchmark regression results are robust.

Table 8. Robustness Test (Lag Two Periods)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Loan_g	Cred_pro	Credit_g	Per_p	Per_g	Ml_p	Ml_g
fin	0.0363*	-0.0019	0.1099	-0.0058	-0.0940	-0.0303	-0.0179
	(1.7814)	(-0.1178)	(1.6229)	(-0.5123)	(-1.3200)	(-0.6233)	(-0.3806)
_cons	2.0822	-0.2467	-12.8577 ***	-0.9716	13.8231 **	-3.5953 **	-3.8658
	(1.1415)	(-0.1782)	(-2.7284)	(-1.4465)	(2.0459)	(-2.0891)	(-0.7360)

controlled variable	control	control	control	control	control	control	control
fixed effect (year)	control	control	control	control	control	control	control
Fixed effect (id)	control	control	control	control	control	control	control
N	273	273	273	273	273	273	273
r2_a	0.0770	0.0775	0.2972	0.1967	0.2218	0.0224	0.1057

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

Table 9. Robustness Test (Reverse Causality Test)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fin	Fin	Fin	Fin	Fin	Fin	Fin
loan_g	0.0159						
	(0.3670)						
cred_pro		0.0208					
		(0.2848)					
credit_g			-0.0123				
			(-0.6158)				
per_p				-0.0677			
				(-0.6092)			
per_g					0.0248		
					(0.6632)		
ml_p						-0.0532	
						(-0.6268)	
ml_g							-0.0185
							(-0.7602)
_cons	0.5812	0.6189	0.6189	0.5685	0.3172	0.6310	0.5663
	(0.2941)	(0.3178)	(0.3149)	(0.2938)	(0.1580)	(0.3209)	(0.2876)
controlled variable	control	control	control	control	control	control	control
fixed effect (year)	control	control	control	control	control	control	control
fixed effects (id)	control	control	control	control	control	control	control
N	364	364	364	364	364	364	364
r2_a	0.1715	0.1715	0.1718	0.1718	0.1725	0.1721	0.1719

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

Heterogeneity Analysis

Compared with large joint-stock banks, small and medium-sized banks are smaller in scale, weaker in strength, weaker in management and operation capabilities, and often have a poorer level of credit structure. On this basis, the application of financial technology will have different degrees of impact in the same direction on the adjustment of loan credit structure, customer structure, and term structure of different types of banks. In order to quantitatively analyze the impact of this heterogeneity, this paper introduces formula (3), typeit is a dummy variable of bank type. The benchmark of this paper is large joint-stock banks. This paper divides the total sample into large banks(annual average asset in local and foreign currencies >= 2 trillion) and small and medium-sized banks (annual average asset weight in local and foreign currencies < 2 trillion), introduce type dummy variables, set large banks as 0 and small and medium banks as 1. The coefficient of typeit × finit mainly used to analyze the difference in the degree of impact of the financial technology on the credit structure of small and medium-sized banks and large banks. The specific results are as follows,

$$loan_{i,t} = \alpha + \beta_0 fin_{i,t} + \vartheta_0 type_{i,t} fin_{i,t} + \lambda_0 control_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (3)$$

Table 10 show that the improvement of the level of fintech has significantly different effects on large commercial banks and small and medium-sized commercial banks. There is no significant difference between the two types of banks regarding the impact on the proportion of medium and long-term loans. In this regard, this paper believes that the impact of financial technology on the allocation of credit resources may be related to the bank's own structure. Generally speaking, the proportion of credit loans, personal loans, and medium-term and long-term loans of small and medium-sized banks (such as regional banks and rural banks in various region) is relatively low, small and medium-sized banks rely more on guaranteed loans, corporate loans, and short-term loans, making the credit structure adjustment of small and medium-sized banks more significant. In contrast, since large banks have a relatively good loan structure, the impact of fintech applications on their credit structure may not be as significant as that of small and medium-sized banks. On the other hand, due to the pressure of interbank competition, small and medium-sized banks are more sensitive to market competition, and will try to reduce capital costs and resist risks by expanding credit scale, while large banks with relatively strong profitability are more cautious.

Table 10. Heterogeneity Analysis of Loan Structure

	(1)	(2)	(3)	(4)	(5)	(6)
	Cred_pro	Credit_g	Per_p	Per_g	Ml_p	Ml_g
fin	0.0421***	0.1323**	0.0437***	0.0550**	0.0349	0.1068*
	(2.7192)	(2.5009)	(3.7114)	(2.2500)	(0.6400)	(1.8389)
fin_type	0.2208***	0.7837***	0.1034*	0.4044**	0.6341	0.5155***
	(6.5579)	(3.2035)	(1.7372)	(2.2616)	(1.4242)	(2.7311)
_cons	-0.2489	4.9340**	0.0495	-7.0122	0.6239	1.9605
	(-0.4458)	(2.1212)	(0.1215)	(-1.4432)	(0.6182)	(0.8046)
controlled variable	control	control	control	control	control	control

fixed effect (year)	control	control	control	control	control	control
fixed effects (individual)	control	control	control	control	control	control
N	455	455	455	455	455	455
r2_a	0.1712	0.3407	0.2677	0.1447	0.0527	0.0800

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

Further Analysis

(1) Mechanism Analysis

According to H5 of this paper, the key to promote credit structure adjustment is to improve banks' information screening capabilities and risk management capabilities, and to increase banks' willingness to issue loans. Specifically, bank financial technology can improve the bank's risk control and information screening capabilities, reduce the level of information asymmetry between banks and enterprises, optimize the bank's credit strategy, and promote the adaptation of corporate financing term structure and investment structure, thereby alleviating the Moral Hazard. The improvement of information screening capabilities can promote banks to collect and process corporate information more accurately and comprehensively. Big data risk control model can detect the financial status of company's business operations in real time, reducing the cost of risk control. The improvement of information screening ability and risk control ability is reflected in the reduction of non-performing loan ratio (Npl) on the bank asset side. The non-performing loan ratio is an important indicator to measure the bank's asset security and information screening ability. Banks with strong information screening ability and risk control ability can control the non-performing loan ratio to the greatest extent. In order to verify this hypothesis, this paper takes the bank's financial technology level as an explanatory variable, and the non-performing loan ratio as an explained variable for regression. Further, at the same time, the non-performing loan ratio is used as an explanatory variable to analyze its impact on the bank credit structure. The regression results are shown in Table 11.

In Table 11, the regression in column (1) examines the impact of fintech on the NPL ratio at the bank level. The results show that the financial technology level has a significant negative relationship with the non-performing loan rate at 1% level, that is, bank financial technology can optimize bank credit risk and reduce the non-performing loan rate. Columns (2) to (7) respectively study the relationship between the non-performing loan ratio and the proportion of credit loans, the growth rate of credit loans, the proportion of personal loans, the growth rate of personal loans, the proportion of medium-term and long-term loans, and the growth rate of medium-term and long-term loans. The results show that there is a significant negative correlation coefficient between the non-performing loan ratio and the above variables, and they are all significant at the 5% level. According to the above regression results, this paper believes that the development of financial technology can improve information identification capabilities, improve risk management level, reduce risk exposure and optimize credit structure. H5 is verified.

Table 11. Mechanism Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Npl	Cred_pro	Credit_g	Per_p	Per_g	Ml_p	Ml_g
fin	-0.0045***						
	(-4.3958)						
npl		-3.7309***	-23.8288***	-2.6840**	-22.9859**	-11.8531**	-15.1072***
		(-2.9208)	(-3.8329)	(-2.5378)	(-2.2914)	(-2.4465)	(-3.0812)
_cons	-0.0556*	0.0587	5.2837**	0.1880	2.4327	1.2288	2.2748
	(-1.6813)	(0.0944)	(2.4332)	(0.4338)	(1.2449)	(1.4881)	(0.9364)
controlled variable	control	control	control	control	control	control	control
fe (year)	control	control	control	control	control	control	control
fe (id)	control	control	control	control	control	control	control
N	455	455	455	455	455	455	455
r2_a	0.1480	0.1163	0.3593	0.2403	0.2804	0.0448	0.0845

Note. t statistics in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

(2) Profitability Analysis

Long-tail clients tend to have higher risk premiums. After the application of financial technology, commercial banks can obtain higher returns in serving long-tail customers, making them more proactive in business sinking. And, this paper further examines whether banks can effectively improve their profitability by using financial technology, and analyzes the relationship between profitability and loan credit structure adjustment. This paper selects net interest margin (Nim) as the proxy variable of bank profitability. The regression results are shown in Table 12.

Column (1) of Table 12 shows the regression results of financial technology level indicators on net interest margins. The coefficient of financial technology indicators is significantly positive and significant at 1% level. Columns (2) to (5) set bank net interest margin as an explanatory variable to regress the proportion and growth rate of credit loans and personal loans. The results show that among the four regressions, only the regression on the growth rate of personal loans is not significant, and the other regression coefficients are all significantly positive, and they are all significant at the 1% level.

The above results show that the use of financial technology can improve the ability of banks to process and use soft information, expand the scale of loan business, and increase profitability by issuing high-yield loans. On the other hand, the improvement of profitability will encourage banks to allocate more loan resources in credit loan business and personal retail loan business, thereby further promote the adjustment of credit structure and retail transformation of commercial banks.

Table 12. Impact of Fintech on Profitability

	(1)	(2)	(3)	(4)	(5)
	Nim	Cred_pro	Credit_g	Per_p	Per_g
fin	0.0059***				
	(4.0871)				
nim		5.096 ***	24.7115***	4.7680***	8.2831
		(3.4299)	(3.3113)	(5.2755)	(1.2973)
_cons	-0.0145	0.6912	6.7563**	0.9491**	4.6576**
	(-0.4200)	(0.9376)	(2.6096)	(2.4710)	(2.4390)
controlled variable	control	control	control	control	control
fe (year)	control	control	control	control	control
fe (id)	control	control	control	control	control
N	365	365	365	365	365
r2_a	0.2350	0.1213	0.3355	0.3967	0.0550

Note. t statistics in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01

Research Conclusions and Policy Recommendations

Using the panel data of 91 commercial banks in China from 2017 to 2021, this paper explores the impact of the application of financial technology on the credit structure of commercial banks in China, and draws the following conclusions:

First, the use of financial technology is conducive to improving banks' information screening capabilities, soft information processing capabilities, and risk management capabilities, and alleviates the problem caused by information asymmetry between banks and borrowers. Specifically, the non-performing loan ratio on the bank's asset side is significantly reduced, so that banks tend to serve more "long-tail customers", boost the willingness and to issue loans, increase the business scale and proportion of credit loans, personal loans, and medium-term and long-term loans, and promote the adjustment and optimization in credit structure, customer and term structure.

Second, with the continuous development of financial technology in commercial banks, the degree of impact of the improvement of financial technology level on the credit structure in different years has obvious differences, and compared with the first year of financial technology (2017), the degree of influence has increased year by year, that is, with the deepening of the development of financial technology, each unit improvement in the level of financial technology will cause different changes in the bank credit structure.

Third, there is a significant difference in the effect of the application of financial technology on large commercial banks and small and medium commercial banks. To a certain extent, compared with large banks, the improvement of the level of financial technology is more effective in optimizing the credit structure of small and medium-sized banks (such as regional banks and rural commercial banks). This may be related to the original credit structure of commercial banks and the pressure of peer competition.

Fourth, financial technology can alleviate the information asymmetry between banks and customers. While bringing more ordinary customers into the scope of services, banks can also effectively control risks, thereby obtaining higher risk premiums and improving profitability. Furthermore, the increase of the bank's operating profit has prompted its business sinking to be more proactive, further promoting the expansion of the bank's loan business and the adjustment and optimization of the credit structure.

Based on the the above research conclusions, this paper puts forward the following policy recommendations:

(1) At the government level, government actively promote the construction of banking financial technology system, enhance the optimization effect of bank financial technology on loan credit structure, customer structure, and term structure, and strengthen the prevention of bank credit risks. The government should actively build new type of digital infrastructure to provide technical support for digital transformation in financial institutions, also build a balanced, agile and efficient data availability center to promote the construction of a secure and fully shared financial network, and accelerate the application of cloud computing technology. At the same time, the government should provide institutional support for bank financial technology innovation, improve innovation risk tolerance, and encourage banks to use new technologies to integrate new businesses.

(2) At the bank level, banks are supposed to actively promote the digital adjustment of the traditional financial service system to meet the needs of digital business, promote the adjustment of the digital business of various departments of the bank, and realize the linkage between the bank's digital department and business technology. Large commercial banks can establish financial technology departments, and small and medium-sized banks can improve their data governance capabilities by cooperating with third-party financial technology companies. Commercial banks should comprehensively promote the business application and technological innovation of financial technology by strengthening the introduction of relevant professionals. On the other hand, banks should speed up the deployment of patents in key areas, increase investment in research and development funds in the field of underlying technologies, and promote the development of financial technology from the underlying to the application.

References

An, B., Zhang, X. R., & An, B. (2019). Research on the strategic transformation of retail banking products based on ' customer-centered '. *New Finance*, *360*(01), 43-56.

Bashusong. (2020). Policy recommendations on solving the current financing difficulties of small and micro operators. *People's Forum Academic Frontiers*, *196*(12), 22-30.

Cheng, M. Y., & Qu, Y. (2020). Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal*, *2020*, 63. https://doi.org/10.1016/j.pacfin.2020.101398

Guo, F., Wang, J. Y., Wang, F., Kong, T., Zhang, X., & Cheng, Z. Y. (2020). Measuring the development of digital inclusive finance in China, index compilation and spatial characteristics. *China Economic Quarterly*, *19*(04), 1401-1418.

He, D. X., Zhang, X. L., Wang, Z. Y., & Bao, H. N. (2020). Monetary policy uncertainty, bank credit and dynamic adjustment of corporate capital structure. *Economic Management*, *42*(07), 5-22.

He, F., & Liu, H. X. (2019). Evaluation of the performance improvement effect of digital transformation of real enterprises from the perspective of digital economy. *Reform*, *302*(04), 137-148.

He, J. (2016). Does deferred executive compensation reduce banks' risk appetite -A study from the perspective of credit asset allocation behavior. *Financial Economics*, *2016*(11), 77-96.

Huang, R., Lai, X. B., & Tang, S. (2020). How does fintech affect corporate financing constraints? -Dynamic effects, heterogeneity characteristics and macro-micro mechanism test. *International Financial Research*, *398*(06), 25-33.

Huang, Y. P., & Huang, Z. (2018). China 's Digital Finance Development, Present and Future. *China Economic Quarterly*, *17*(04), 1489-1502.

Jiang, F. W., Hu, Y. C., & Huang, N. (2021). Central Bank Monetary Policy Report Text Information, Macroeconomic and Stock Markets. *Financial Research*, *492*(06), 95-113.

Jiang, S. X., & Liu, Z. L. (2016). Does capital quality affect bank loan behavior? *Financial Research*, *438*(12), 63-77.

Jin, H. F., Li, H. J., & Liu, Y. L. (2020). Financial Technology, Bank Risk and Market Crowding-out Effect. *Financial Research*, *46*(05), 52-65.

Li, C. T., Yan, X. W., Song, M., & Yang, W. (2020). Financial Technology and Enterprise Innovation-Evidence from New Third Board Listed Companies. *China's Industrial Economics*, *382*(01), 81-98.

Li, Y. F., Li, M. L., & Li, J. (2022). Bank financial technology, credit allocation and corporate short-term debt long-term use. *China's Industrial Economics*, *415*(10), 137-154.

Li, Z. F., Chen, J. J., Lian, Y. J., & Li, M. J. (2022). Economic policy uncertainty and corporate short-term debt. *Management World*, *38*(01), 77-101.

Lin, Y. F., & Li, Y. J. (2001). Development of Small and Medium-sized Financial Institutions and Financing of SMEs. *Economic Research*, *2001*(01), 10-18.

Liu, M. F., & Jiang, W. (2020). Does financial technology promote or hinder the efficiency of commercial banks ? - An Empirical Study Based on Chinese Banking. *Contemporary Economic Science*, *42*(03), 56-68.

Lu, Z. Y., & Ma, H. (2021). Research on the impact of fintech innovation on real economic growth. *Scientific Management Research*, *39*(05), 150-159.

Mona, & Su, Q. (2020). Crowding-out effect or catfish effect, A study on the impact of fintech on traditional inclusive finance. *Modern Finance*, *40*(01), 56-70.

Mona, S. Q., & Lei, H. B. (2020). How Fintech Affects Banking Competition. *Financial Economy*, *41*(03), 66-79.

Qiu, H., Huang, Y. P., & Ji, Y. (2018). The impact of FinTech on traditional banking behavior is based on the perspective of Internet financial management. *Financial Research*, *461*(11), 17-29.

Shen, Y., & Guo, P. (2015). Internet Finance, Technology Spillover and Total Factor Productivity of Commercial Banks. *Financial Research*, *417*(03), 160-175.

Song, Q. Y., Li, X., & Qian, L. (2019). Economic policy uncertainty and corporate loan costs. *Financial Research*, *469*(07), 57-75.

Tang, S., & Xie, X. Y. (2021). Yow do corporate holding financial institutions serve the real economy Based on the perspective of supply chain spillover effect. *China's Industrial Economics*, *404*(11), 116-134.

Xu, X. P., Li, H. J., & Ge, Y. F. (2021). Can the application of financial technology promote the adjustment of bank credit structure ? - Quasi-natural experimental study based on bank's external cooperation. *Financial Research*, *47*(06), 92-107.

Yu, B., Zhou, N., & Huo, Y. Q. (2020). The impact of fintech on the profitability of commercial banks-Empirical test based on dynamic panel GMM model. *Southern Finance*, *523*(03), 30-39.

Zhang, J. Q., Li, K. L., & Zhang, J. Y. (2022). How does bank fintech affect corporate structural deleveraging? *Financial Research*, *48*(01), 64-77.

Zhao, H. R., Li, K. W., & Wang, F. F. (2019). Theoretical, path and empirical research on the strategic transformation of commercial banks. *Research on financial supervision*, *89*(05), 47-69.

Zhong, N. H., Liu, Z. K., He, J. X., & Su, C. L. (2016). Structural problems of corporate debt in China. *Economic Research*, *51*(07), 102-117.