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A quantitative analysis study of FinTech on banks' operational efficiency and risk management based on Monte Carlo simulation

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ABSTRACT

Fintech has not only greatly improved the operational efficiency of banks by introducing cutting-edge technologies such as big data, artificial intelligence, and blockchain, but also posed new challenges to banks' risk management. This paper uses Monte Carlo simulation to explore the impact of fintech on banks' operational efficiency and risk management. A VaR data model is used to analyze the impact of fintech on the operational efficiency of three types of commercial banks: big five banks, joint-stock banks, and city commercial banks. The non-performing loan ratio of China MS Bank is used as the empirical object for quantitative analysis of bank risk management. Monte Carlo simulation is used to realize the VaR calculation of banks' NPL ratio. The empirical analysis finds that the impact of fintech on the operational efficiency of all three types of commercial banks is relatively significant, but there are differences in direction and lag period. Meanwhile, FinTech increases banks' NPL ratio. It shows that fintech has a negative impact on bank risk management, for this reason, this paper develops relevant strategies to deal with the risk challenges brought by fintech according to bank types.

Keywords: Fintech, Monte Carlo simulation, VaR, Operational efficiency

1. Introduction

The term "fintech" was formally coined in 2011 to refer to the application of technological innovations in the financial sector [1-2]. In 2014, the Chinese government work report mentioned "fintech" for the first time, in March 2016, China's financial regulators defined the term "fintech", and in August 2019, the People's Bank of China (hereinafter referred to as the "central bank") released a fintech development plan for the next three years to further integrate fintech and risk management and promote the in-depth promotion of risk management [3-5]. On the one hand, FinTech has improved the efficiency of financial services, making financial transactions and financial operations more convenient through innovations such as digital payments, e-money, and smart investment advisors [6-7]. On the other hand, the rise of fintech

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has also brought a series of challenges, with cyber information security, regulatory and compliance challenges becoming important issues for financial institutions [8-9].

Under the background of today's era of rapid development of information technology, financial technology is gradually penetrating into various fields of the financial industry, and its efficient, convenient and innovative characteristics are becoming more and more significant, which has a profound impact on the operation of the financial market and the provision of financial services [10-12]. As one of the key components of China's financial system, commercial banks are experiencing unprecedented opportunities and threats in the face of the impact of fintech trends [13]. On the one hand, the rapid advancement of fintech has brought many difficulties to the banking industry's environmental changes and trends, which further aggravates the "survival pressure" of commercial banks. But on the other hand, the rise of fintech can push commercial banks forward, forcing them to transform and upgrade to meet the challenges of competition [14-16].

With the rapid development of technology and the continuous evolution of the financial industry, commercial banks have unprecedented opportunities and challenges in the wave of digital transformation. The rise of fintech not only promotes the innovation and efficiency of banking business, but also brings many complex risk management challenges [17-19]. In this context, risk management has become a crucial topic in the digital transformation of commercial banks. In the current era of constant change, deepening the understanding of risk management in commercial banks will help commercial banks adapt more flexibly to the future development trend of the financial industry and safeguard the stability and sustainable development of the financial system [20-21].

The rapid development of fintech has gradually come into people's lives, and the research around fintech is also very popular and broad, in which the mainstream research direction of fintech is mainly financial decentralization, digitization, etc., and involves the scope of business mainly, payment, cryptocurrencies and so on. Literature [22] tries to define fintech as an interdisciplinary category that integrates finance, technology management and innovation management, and divides the practice of fintech into four major categories, namely, payment, consulting, financing, and compliance, and explores the business value of fintech in depth, which provides valuable references for fintech researchers. Literature [23] reviewed the research papers related to FinTech, emphasized that FinTech has attracted much attention, and concluded that FinTech promotes the digital transformation of the financial industry. Literature [24] conceptualized a FinTech innovation mapping strategy to assess the extent to which FinTech has driven transformation in the financial sector, involving payments, cryptocurrencies, blockchain technology applications, and cross-border payments. Literature [25] explores decentralized financial technologies in FinTech, noting that financial district centrality has undermined the accountability system and weakened the ability of traditional financial regulation and enforcement in the traditional financial sector, and argues that financial district decentralization promotes an entirely new approach to financial regulation based on the concept of embeddedness. Literature [26] summarizes the innovative business functions and innovative practices of digital finance, while looking forward to the future development trend of fintech based on digital technology, and mainly studies the digital financial cube, covering the core three dimensions of digital finance and fintech, which fills the research gaps in related fields. Literature [27] evaluates the benefits, business models and potential challenges of decentralized finance, and argues that financial decentralization has rebuilt the modern and content system to a certain extent, creating a landscape of entrepreneurship and innovation.

The impact of fintech on banks is very significant and broad, involving banks' risk management ability, profitability, service efficiency, etc., and may even have a substantial impact on the ecological position of banks in the financial system. Therefore, it is necessary to study how FinTech affects banks and the logic mechanism of the specific role of FinTech. Literature [28] based on the bank's perspective, reviewed the relevant research papers on fintech services, argued that fintech lending institutions can not completely replace the bank's function, which is due to the bank's own research and development of fintech as well as the bank's cooperation with the fintech enterprise is underway, and finally showed the impact of external factors such as regulation, geopolitics and other external factors on the future development of the bank. Literature [29] reveals that FinTech to a certain extent contributes to the improvement of commercial banks' profitability, risk management and financial innovation ability, and also improves the efficiency of commercial banks' services and traditional business models, etc. In short, FinTech has a positive significance for the improvement of the comprehensive ability of commercial banks. Literature [30] empirically analyzes how fintech affects banks' risk-taking ability based on panel data at the level of unbalanced banks in China, and the study shows that finance and technology have exacerbated the risk-taking situation of banks due to the deterioration of asset quality brought about by the fintech boom, and the two generally show an inverted U-shaped relationship. Literature [31] used case study methodology to compare and analyze the strategies and product innovations of Industrial and Commercial Bank of China (ICBC) and Citibank in the context of the fintech boom, in order to deeply analyze the challenges and obstacles faced by China's banking industry, and put forward suggestions to improve and optimize the implementation of the concept of the core power of technology into the development and competition of banks. Literature [32] analyzed the data related to the financial market in Indonesia and pointed out that the growth of fintech companies is negatively correlated with the performance of banks, and proved the results based on the additional test and robustness test, i.e., fintech has a negative impact on the performance of banks. Literature [33] combines patent data, fintech development index and generalized moments modeling tools to reveal that fintech innovations generally reduce bank profitability as well as asset quality, but fintech has a positive impact on bank capital adequacy and managerial efficiency, and points out that banks should pay more attention to fintech practices and innovations rather than to competitors' behavior.

The study constructs a VAR model to investigate the impact of fintech on banks' operational efficiency through Monte Carlo simulation method. First, the quantitative analysis part of bank operational efficiency constructs a VAR model based on relevant variables. The model describes the dynamic relationship between fintech and the operational efficiency of three types of commercial banks: big five banks, joint-stock banks and city commercial banks. Second, the quantitative analysis of risk management part, taking the NPL ratio as a quantitative indicator of risk management, three VaR models for measuring banks' NPL ratios, namely, white noise process, first-order autoregressive process, and general autoregressive process, are built. Taking the NPL ratio data of China MS Bank as an example, the three established measurement models are simulated and the impact of fintech is empirically analyzed. Finally, some relevant measures are proposed on how banks can strengthen risk management and prevent credit risk.

2. Specific impact of fintech on banks

2.1. *Financial technology*

Financial technology, namely "finance + technology", refers to the financial institutions through modern information technology to transform the traditional financial business service model, financial tools, and innovative financial products, service structure, the main science and technology for the Internet technology, big data, cloud computing, artificial intelligence, security technology, etc., which are comprehensively applied in the six major financial areas of payment, clearing, lending and financing, wealth management, retail banking, insurance, transaction settlement, so as to achieve the deep integration of finance and technology. Clearing, lending and financing, wealth management, retail banking, insurance, trading and settlement of the six major financial areas, so as to realize the deep integration of finance and science and technology [34].

2.2. *Impact of FinTech on banks' operational efficiency*

2.2.1. Accurately portraying user profiles. The rapid development of financial technology has enabled Internet technology, computer technology and artificial intelligence technology to be widely used in financial business and product innovation, providing strong technical support for the innovative development of banks. The development of financial technology can help banks carry out digital reform, fully apply big data technology for customer information management, through big data technology, cloud computing technology, etc. applied to the management of financial customers, to create a huge user database, and through the technology of big data technology mining and analysis functions to extract customer information, preferences, accurate portrayal of the user profile, for banks to provide more targeted financial services Lay the foundation for banks to provide more targeted financial services.

2.2.2. Stimulating entirely new financial needs. The development of financial technology has greatly promoted the innovation and development of banking business and products, and has made the demand for more convenient, low-threshold, and simple financial services and products increase rapidly, stimulating the formation of new financial needs, effectively promoting the business and product innovation of banks, and broadening the target service groups of banks, so that they can pay attention to more scattered small customers, and carry out convenient financial business operations through Internet platforms and corresponding technologies.

2.2.3. Reduced transaction cost charges. Fintech itself is an innovation in the financial field, optimizing the financial business operation process and lowering the service threshold of financial business and products through the extensive application of various modern information technologies. The extensive application of Internet platforms and big data technologies greatly weakened the information asymmetry between the two sides of the transaction, making it possible to reduce the transaction costs and expenses of the two sides of the transaction, and to reduce a variety of risk costs, including information asymmetric matching costs, default costs and additional costs caused by moral risks, etc.

2.2.4. Innovative means of payment. The development of fintech has changed the traditional functions and roles of banks' credit intermediaries and payment intermediaries, and the payment intermediary functions of banks have been greatly weakened, and various third-party payment methods relying on the Internet and blockchain technology have replaced the payment intermediary functions of banks and become the most important Internet payment intermediary methods at present. As a result, fintech has greatly revolutionized the means of payment, and the upgrading of payment intermediaries has greatly improved the efficiency and timeliness of payment, resulting in a rapid arrival time of funds, a significant increase in the efficiency of financing, and an increase in the convenience of financial business operations. Both parties to a financial transaction only need to complete the transaction through the third-party business platform, after completing the identification, and the funds arrive in real time, which greatly reduces the cost of the transaction, and provides a more convenient payment channel for the development of various financial businesses of banks.

2.3. *Impact of FinTech on banks' risk management*

2.3.1. Impact on traditional financial services. The development of financial technology has greatly impacted the traditional financial services of banks, and the most affected traditional financial businesses include deposit and loan business and wealth management business. Some fintech enterprises relying on advanced technology and convenient financial product supply have attracted a large proportion of decentralized and small customers excluded by banks by providing financial products characterized by low threshold, convenient operation and high returns.

2.3.2. Undermining the strengths of financial intermediation. With the development of financial science and technology, various advanced technologies have been applied to information collection, mining and analysis, and the information platform established has greatly weakened the information asymmetry between the two sides of financial transactions, thus weakening the advantageous position of banks in the transmission of information. In addition, the convenient operation on the cell phone makes it unnecessary for customers to go to the bank in person, fill out complicated application forms, business forms, and complete the cumbersome procedures, and the convenient and fast transaction platform and means make the bank's payment intermediary advantage lost.

2.3.3. Introduction of technical operational risks. The essence of financial technology is the integration and development of finance and modern information technology, while modern information technology is still in the process of continuous development, and some of the information technology itself has certain information security and operational risks. Therefore, when banks introduce financial technology, they also introduce corresponding technical risks. Financial technology is extremely dependent on the Internet, and all kinds of financial services also need to be completed on the Internet, which may give rise to risks such as network information security and computer operations, technical failures, algorithmic errors, etc. In the event of technical errors, this may lead to the emergence of problems such as loss of information and failure of online payment transactions.

3. Monte Carlo simulation

Monte Carlo simulation is an analytical and computational method for VaR models. Monte Carlo simulation is a method of generating time series iteratively by setting up a stochastic process, calculating parameter estimates and statistics, and then investigating the characteristics of their distributions [35].

3.1. *Meaning of VaR*

The basic meaning of VaR is the value of the maximum loss that a financial asset or portfolio of assets can suffer, given a confidence level, under normal market volatility and over a certain holding period [36]. Its mathematical expression is: $VaR[X;p]=F_x^{-1}(p)$, where $F_x^{-1}(p)=\inf\{x\in R \mid F_x(x)\ge p\}$.

When the loss of an asset X follows a continuous distribution, there is $\Pr(X\le Q_p)=p$, i.e., $F_x^{-1}(p)=Q_p$. In practice, the quantile Q_p represents the value at risk, also known as the quantile risk measure. It can also be expressed as the probability that, at a given confidence level α and holding time Δt, there is a $1-\alpha$ chance that the loss of the asset will not exceed a specific VaR value during the Δt time period, which is expressed by the formula: $\Pr ob(\Delta P>VaR)=\alpha$ or $\Pr ob(\Delta P<VaR)=1-\alpha$. Where: $\Pr ob$ represents the probability that the loss of the value of the asset is less than the upper limit of the possible loss. ΔP represents the amount of loss in value of the financial asset over the holding Δt period. α indicates the confidence level.

1)VaR can be expressed in two ways:

(1) Absolute VaR value. The difference between the initial value of the portfolio and the value at the end of the investment period at a certain confidence level indicates the absolute loss relative to the initial value. The formula is expressed as follows:

$$V(zero)=V_0-V^*=V_0-V_0(1+R_L)=-V_0R_L \tag{1}$$

where V_0 represents the initial value of the portfolio. V^* represents the end value of the investment period. R_i indicates the rate of return for the investment period under certain confidence level conditions.

(2) Relative VaR value. The difference between the expected value of the portfolio and the end value of the investment period, expressed relative to the expected return on the opportunity to lose. The formula is shown below:

$$V(mean)=E(V)-V^*=V_0(1+\mu)-V_0(1+R_L)=V_0(\mu-R_L) \tag{2}$$

where $E(V)$ denotes the expected value. μ represents the expected rate of return.

There are two main factors that affect the VaR value: the size of the confidence level α and the length of the holding period Δt. The determination of the α size depends mainly on the risk manager's attitude to risk, which is generally taken as 90% to 99.9%. The determination of Δt depends mainly on the liquidity of the assets in the financial portfolio, which is generally taken as a target period of l days, 1 week, 10 days or 1 month.

For confidence level α: the larger α is, the larger the resulting VaR will be. Moreover, as α increases, there will be fewer loss events greater than the VaR, but the risk of such a small probability of occurrence but a large loss is not measured. Also, VaR is affected by the number of samples; if there are 1000 sample values, then 99% of VaR indicates the 10th lowest observation, 99.9% of VaR indicates the lowest one, and there is no way to calculate the 99.99% of VaR value. When VaR is used as a value at risk to prevent insolvency, then it is better to use a higher confidence level and prepare sufficient capital to ensure that insolvency does not occur. In practice, α is not selected as high as possible; if a confidence level of 99.99% is selected, then a loss event that exceeds the VaR occurs only once in 10,000 trading days, or once every 40 years, which lacks practical operational significance.

For Δt: The larger Δt is, the larger the VaR value is. Extending the VaR value for one day to the VaR value for T days requires the assumption that the daily returns are constant for T days, i.e., that the distribution of returns is independently stationary, and the normal distribution conforms to this characterization, and thus yields: $VaR(T\ day) = VaR(1\ day) \times \sqrt{T}$. If one is trying to compute the risk of an unfavorable scenario, then a smaller time period should be taken. If one is to calculate how much capital should be retained to prevent insolvency, then it is recommended that a larger time period be used.

2)As a risk management tool, the VaR method has been widely used in various financial fields in recent years. The most important of them are manifested in two aspects:

(1) Financial capital regulation. The VaR value measures three different risks, market risk, credit risk and operational risk, in the same method, realizing the risk summation of the categories between different risks of different assets in the asset portfolio, which is conducive to controlling the overall risk of banks and financial institutions.

(2) Investment performance assessment. Since financial investment has high risk and high return, financial institutions introduce the VaR value into the performance assessment system as a risk indicator for the purpose of sound operation, and make risk adjustments to returns so that they can effectively avoid excessive speculation.

3.2. Calculation of VaR

There are two different types of models for the calculation of VaR models, the parametric method and the non-parametric method. The parametric method mainly includes three kinds of models such as normal method, Monte Carlo simulation method and historical data method.

The Monte Carlo simulation method assumes that the price change of financial assets conforms to a certain stochastic process, i.e., a suitable probability distribution model is constructed first, so that the solution of the required problem is exactly the parameter of the model, and then a computer program is used to simulate, that is, to make a statistical test, to obtain the corresponding simulation value, so as to get the distribution of the return of the financial assets, and to calculate the value of VaR. The specific calculation steps are shown below: first, choose the asset price stochastic model. Usually the most commonly used stochastic model is the geometric Brownian motion, which assumes that the various assets at different times are uncorrelated with each other, and can be expressed by the formula:

$$dS_t = \mu_t S_t d_t + \sigma_t S_t dz \tag{3}$$

where dS_i denotes the amount of price change, μ_i denotes the return on the asset, σ_i denotes the standard deviation, z denotes the Wiener process, $dz = \varepsilon\sqrt{dt}$ obeys a normal distribution with an expectation of 0 and a variance of dt, ε is a random variable obeying a normal distribution, and dt denotes the change in time. Secondly, a sequence of random variables ε is generated, $\varepsilon \in N(0,1)$ then, assuming that parameters μ_i and σ_i are constants, ε, μ_i and σ_i are substituted into the above equation to derive the path of change in the asset price, and the return can be calculated from $\Delta S_t / S_t$: Finally, the second and third steps are repeated a number of times to obtain the probability distribution of the asset price, and the corresponding VaR value is calculated based on this probability distribution.

4. Empirical analysis

4.1. *Quantitative analysis of banks' operational efficiency*

In order to further verify the extent of the impact of fintech on the operational efficiency of banks, this paper selects the financial statements of 14 sample banks for the 12-year period from 2012 to 2023, and applies the VaR data model to study the impact of fintech on the operational efficiency of three types of commercial banks. Due to the need of the research, this paper uses Eviews 6.0 software to analyze the relevant data.

4.1.1. Selection of variables. BANK PERFORMANCE: Banks are affected by FinTech differently due to their different business strategies, capital size and capital business structure. Therefore, this paper takes the performance scores of three types of commercial banks (five major banks (FBB), joint-stock banks (SCB) and municipal commercial banks (MCB)) as the dependent variable in order to study the difference in the impact of FinTech on the operational efficiency of each type of bank.

Fintech scale (FTS): this paper adopts the fintech scale indicator as the independent variable.

Macroeconomic indicators (HG): macroeconomic conditions affect all industries and have a significant impact on the performance of commercial banks. Among the many indicators reflecting macroeconomic performance, GDP is the most intuitive and representative indicator. In this paper, GDP is also selected as a macroeconomic indicator, and its growth rate data is used as a control variable.

4.1.2. Descriptive statistics of variables. The descriptive statistics of the selected variables are shown in Figure 1. The fluctuation of the performance of the five largest banks and the scale of FinTech is large, and its standard deviation is 8.26 and 8.17, respectively. The fluctuation range of the performance level of the five largest banks, the joint-stock banks and the city commercial banks is large, and the interval reaches 33.21, 34.36, and 23.62, respectively. The change of the macro factor is also large, and there is a large increase in the end of the statistical period compared with the beginning of the period, which reflects the developmental achievements of the economy.

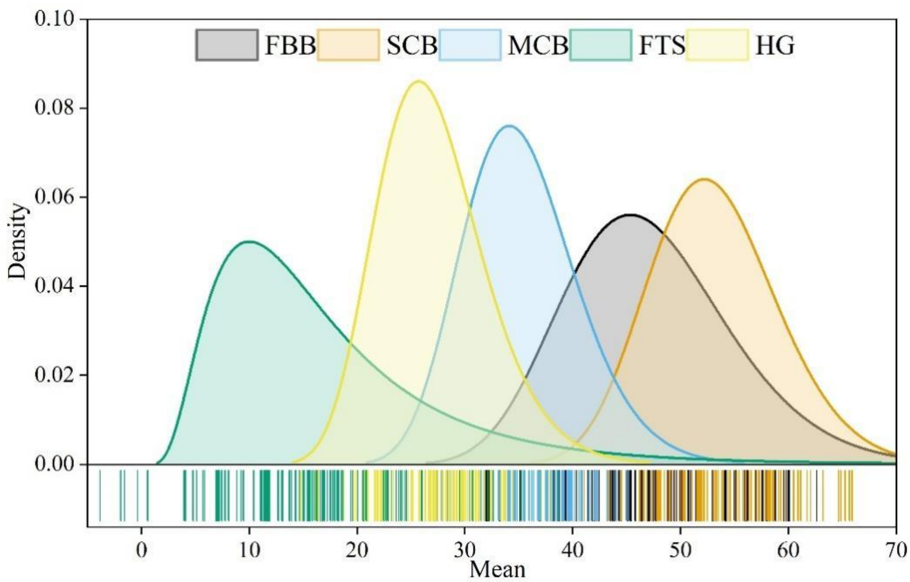

Fig. 1. Select the descriptive statistics of variables

4.1.3. Model setup. The VaR model examines the dynamic relationship between the variables and is generally of the form shown in Equation (4):

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \tag{4}$$

Where, Y is the K-dimensional vector of endogenous variables, A denotes the corresponding coefficient matrix, P is the lag order of endogenous variables, and ε_t is the error vector.

Since the data selected in this paper are from 2012 to 2023, the frequency is low, so this paper utilizes EVIEWS software to convert the data into quarterly high-frequency data, so that the data have the original 12-year data changed to data from the fourth quarter of 2012 to the fourth quarter of 2023, and there are 45 observations for each variable. At the same time, in order to eliminate the problem of heteroskedasticity, this paper adopts the logarithmic processing method for the data.

4.1.4. Stability test and lag order determination. Prior to modeling, unit root tests are required for time series variables to detect whether the variables are smooth or not, otherwise, direct regression may result in "pseudo-regression" phenomenon. There are several methods for unit root test, including LLC, Hadri, Brdtung, IPS, Fisher-PP and Fisher-ADF. In this paper, we will use the ADF test to test the variables, found that the original data of each variable is not significant at the 5% confidence level, that is, the variables exist unit root, is a non-stationary sequence, and the VAR model needs the sequence to be a smooth sequence, so this paper is the first-order difference of the data to deal with the change to test the smoothness of the data. The results of unit root test of each variable are shown in Table 1. Each variable passes the smoothness test at 5% confidence level.

Table 1. Test results of each variable unit root

Variable	ADF statistics	Probability value	Test result
DLFBB	-5.63544	0.0000	Smoothness
DLSCB	-6.55223	0.0012	Smoothness
DLMCB	-3.25565	0.0000	Smoothness
DLFTS	-7.45523	0.0021	Smoothness
DLHG	-8.56563	0.0000	Smoothness

After passing the smoothness test, the data can be modeled statistically using the first-order difference after data, but the number of model lag orders also needs to be determined in modeling. According to economic theory, generally quarterly data after 4 periods, monthly data lagged 12 periods, this paper proposes to use the lag order of 4. The lag period is determined as shown in Table 2, * indicates that it is significant at the 5% confidence level. The optimal lag order for the equation model is also found to be 4 by performing the likelihood ratio test (LR), final prediction error (FPE), AIC information criterion, SC and HQ criterion on the variables.

Table 2. Late period determination

Lag	LogL	LR	FPE	AIC	SC	HQ
0	271.8311	NA	9.63E-13	-13.46036	-13.46603	-13.43003
1	296.1339	41.26068	1.12E-12	-13.41399	-12.08634	-12.93901
2	338.8156	30.00965	1.27E-12	-13.21688	10.90967	-12.41224
3	345.8991	33.90442	1.36E-12	-13.57761	-10.00285	-12.38531
4	472.2115	127.8545*	7.19e-15*	-18.05258*	-14.54523*	-16.24543*

4.1.5. VAR model regression. Vector autoregressive models of three types of commercial banks' performance with fintech and macro factors were established to describe the dynamic relationship between them respectively, and the lag order of four periods was selected for autoregression, and the regression results are shown in Table 3. Observation of the estimated results of the VAR model reveals that FinTech has the most significant impact on the five largest banks at a lag of four periods (-0.383527***), and the relationship is more pronounced at a lag of two periods (-0.052389*), which is partly attributable to the overly large size of the five largest banks. Joint-stock commercial banks are most significantly affected at one period of FinTech lag (-0.05456**), and similar to the five banks are affected by the reverse impact of FinTech. Similar to joint-stock banks, city commercial banks are also most significantly affected at the one-period lag of fintech, and the degree of significance of the impact decreases over time, but unlike the five major banks and joint-stock commercial banks, they are positively affected. At the same time, the constructed macro-factors have an impact on all three types of commercial banks, but the lag of significant impact is different, in which the smaller the size of the bank is affected by the shorter lag, the more significant the impact, and the five big banks are affected by the macro-factors at a lag of three and the impact of the significance of the impact of the poorer.

Table 3. VAR model test results

	DLFBB	DLSCB	DLMCB
DLFTS (-1)	-0.03052	-0.05456**	0.174154**
DLFTS (-2)	-0.052389*	0.019582*	0.093718*
DLFTS (-3)	-0.03482	-0.03464	0.115673*
DLFTS (-4)	-0.383527***	0.01747	0.02818
DLHG (-1)	0.22519	0.1541	-0.21231*
DLHG (-2)	-0.13843	-0.0216888**	0.03865
DLHG (-3)	0.019585*	0.03207	-0.010023***
DLHG (-4)	-0.01441	0.093634*	-0.049582*

4.1.6. Granger causality tests. After the estimation of the model, a Granger causality test is also performed on the variables to determine if there is a causal relationship between the variables. The results of the Granger causality test are shown in Table 4. When conducting the causality test for each variable, it is found that the long-term causality between fintech and the business performance of the three types of banks is significant at the 10% level, i.e., the size of fintech is the Granger cause for the five largest banks, joint-stock banks and city banks, while the causality between fintech and the five largest banks is the most significant. The causality of the macro factor is not significant for the five largest banks, which is more consistent with the model estimation results above. The causality of the macro factor with joint-stock banks and city banks is significant at the 5% level, i.e., the Granger cause of joint-stock banks and city banks when the macro factor.

Table 4. Granger causality test results

Dependent variable: DLFBB			
Excluded	Chi-sq	df	Prob.
DLFTS	18.34037	4	0.0511
DLHG	6.59406	4	0.1569
Dependent variable: DLSCB			
Excluded	Chi-sq	df	Prob.
DLFTS	8.2498	4	0.0763
DLHG	16.22357	4	0.0027
Dependent variable: DLMCB			
Excluded	Chi-sq	df	Prob.
DLFTS	8.66571	4	0.0459
DLHG	10.3188	4	0.0825

4.1.7. Analysis of empirical results. In the case of growing fintech, the reverse impact of fintech on the five largest banks has become more and more obvious, and although their strong capital strength has defused part of the impact, their operational efficiency still shows a gradual downward trend. Joint-stock banks vigorously engage in business innovation and participate in new fintech businesses at a faster pace with a shorter lag period. Business-concentrated city banks strictly control fintech risks and have a higher degree of direct participation, which enables them to reap the benefits from the fintech system faster. In addition, the model results also found that the constructed macro factor has a more significant impact on smaller banks, while the five largest banks are affected but the test results are not significant, indicating that the larger the bank's ability to resist the risks posed by macroeconomic fluctuations is also greater.

4.2. Quantitative analysis of banks' risk management

In this paper, the non-performing loan ratio of MS Bank is studied. The data is obtained from the 2021 annual report of China MS Bank Co. Non-performing loan ratio refers to the share of non-performing loans in the total loan balance of a financial institution. NPLs are loans categorized into five categories of normal, concern, substandard, doubtful and loss based on risk basis in assessing the quality of bank's loans, where the last three categories are collectively referred to as non-performing loans. Under a certain level of confidence, the maximum possible value of a commercial bank's NPL ratio after one year can be used as a measure of the maximum value of the bank's loans in a year that will be lost in the coming year. Based on the maximum predicted value of the NPL ratio (under a certain level of confidence) it is possible to estimate a reasonable economic capital and credit risk reserve. Based on this idea, we can then apply Monte Carlo simulations to calculate the VaR of the NPL ratio at a given confidence level.

4.2.1. Selection of model parameters. Since it is not possible to obtain enough historical data from public sources, the parameters of the model in this paper can only be roughly determined by relying on qualitative analysis (statistical characteristics of the parameters as well as their economic significance) and simulated trial calculations.

1) Selection of calculation time period. In the process of calculation, this paper takes the quarter as the time period, i.e., the NPL ratio at the end of the previous year is the initial value, and four simulations are conducted to obtain the NPL ratio at the end of the current year.

2) Selection of standard deviation σ of white noise ε_i. In this paper, the VaR value of the NPL ratio is used to measure the loan risk status of the market under normal fluctuations and the time period chosen is a quarter, so the fluctuation of the macro market factor should not be too large in the simulation calculation. e^s reflects the ratio of the cumulative impact of the previous period's NPL ratio on the current period, and this value should not take on an excessively large value and should float around 1. In order to determine

the standard deviation σ of the white noise ε_t, order $r_i = \varepsilon_t$, 5000 simulation trial calculations are carried out with Crystal Ball for e^{r_i} when σ takes different values. Based on the 5000 trial runs, this paper determines that the standard deviation σ of the white noise process ε_t is taken to be 0.05. This is because when σ it is taken to be 0.05, the change in the NPL ratio over a quarter is at the 20% level, which is an acceptable and reasonable result.

When σ is taken to be 0.1, this variation reaches 40%. When the value of 0.2 is taken, this variation is nearly doubled, so 0.05 is selected for σ.

3) Selection of coefficient a in the process of $AR(1)$. Compared to the simple white noise process, the $AR(I)$ process is slightly more complex: at $0 < a < 1$, the $AR(I)$ process is smoother, and the coefficient a allows for a certain degree of continuity in the variation. At $a \geq 1$, the process is no longer stable and shows a trend. At $-1 < a \leq 0$, the process is more uneven than a random walk, as the value of the coefficient a gives it a tendency to move in the opposite direction of continuity. At $a \leq -1$, the process displays a stronger oscillatory character.

After the above analysis, we can first determine that the range of values of a should be $0 < a < 1$. On further analysis, as a gets closer to 0, the closer the $AR(1)$ process is to the white noise process, and such a value loses the significance of choosing different processes for comparison. In addition, if we consider its economic significance, assuming that the market is in a smooth and normal fluctuation state, the value of the market factor should not change much in each period, so we choose $a = 0.9$ (far from 0, close to 1).

4) Selection of the coefficient b in the process $ARMA(1,1)$. Here a is the same as in the above, i.e., $a = 0.9$. Similarly, σ is chosen with the same value as above. To determine the value of b, we choose different values of b and simulate the computation to obtain e^{t_i}. e^{t_i} is not sensitive to the value of b. In particular, the range of values for e^{t_i} hardly changes when b is taken from 0 to 1. Considering the economic significance of b, which reflects that the unanticipated fluctuations in the previous period continue to affect the market factor into the current period, the ability to influence should not be large, so b is taken as 0.2.

5) Final form of the model. The final form of the model is determined as:

$$In(H_l) = In(H_{l-1}) + r \tag{5}$$

Among them:

White noise:

$$r_t = \varepsilon_t \tag{6}$$

$AR(1)$:

$$r_t = 0.9 r_{t-1} + \varepsilon_t \tag{7}$$

$ARMA(1,1)$:

$$r_i = 0.9 r_{i-1} + 0.2 \varepsilon_{i-1} + \varepsilon_i \tag{8}$$

Taking equation (5) as the basis, and then taking the actual value of the NPL ratio at the end of 2019 and the end of 2020 as the initial value, substituting the specific data into the expressions of (6), (7), and (8), respectively, and applying Monte Carlo simulation method, simulating and calculating the NPL ratios at the end of 2021 and the end of 2022, the number of simulations is taken as 5,000 times, and the confidence level is taken as 99% and 95%.

4.2.2. Comparison of calculation results. The comparison of the statistics of the three stochastic processes with the simulated values of the prediction results is shown in Table 5. The actual values at the end of 2019 and 2020 are 0.66% and 0.57%, respectively. In the three simulation processes, the predicted values obtained through the calculation of this paper are larger than the actual values to a certain extent, so that the prediction results are also more in line with the actual situation. For banks, the predicted value of the NPL ratio is higher than the actual value, reflecting the principle of maintaining prudent treatment in controlling bank risks. The whole simulation process can be seen, the three stochastic process in all aspects of the conclusion of a common characteristic: affect the results of the various statistical quantities in accordance with the order of the size of the value, from the smallest to the largest are the characteristics of the white noise process is the smallest change, and then followed by the $AR(1)$ process and the $ARMA(1,1)$ process. 5000 simulation of the data to choose a different value as the initial value of the results are the same. It can be concluded that if different stochastic processes are chosen, it will cause different magnitude of fluctuations in the market factor.

Table 5. Simulation results and comparison (Unit/%)

	At the end of 2019 at (0.87)				At the end of 2020 at (0.63)			
	SD	M	VaR		SD	M	VaR	
			95%	99%			95%	99%
White noise	0.0754	0.8601	0.9664	0.9873	0.0568	0.7165	0.0754	0.8601
$AR(1)$	0.0736	0.8683	0.9709	0.9971	0.0957	0.7529	0.0836	0.8683
$ARMA(1,1)$	0.1202	0.8694	0.9803	1.0765	0.0996	0.7592	0.1202	0.8694
Actual value	0.66				0.57			

4.2.3. Analysis of the impact effect of FinTech. The analysis above proves that the model can predict the NPL rate in line with the actual situation. In this subsection, the model will be used to predict the NPL ratio after the addition of fintech as a way to determine the impact of fintech on banks' risk management. Using the NPL ratio of China MS Bank at the end of 2021 (0.71%) under the influence of fintech as the initial value, brought into Equation (5), and simulated 5000 times for each of the three stochastic processes using Crystal Ball software, the predicted value of the bank's NPL ratio at the end of 2022 is obtained as shown in Table 6. There is a 95% chance that China MS Bank's NPL ratio will be less than 0.7369% (white noise process), 0.7963% (first-order autoregressive process), and 0.7988% (general autoregressive moving average process) at the end of 2022. There is a 99% chance that it is less than 0.7422% (white noise process), 0.8031% (first-order autoregressive process), and 0.8055% (general autoregressive moving average process), and all six predicted values are greater than 0.71%. From the above analysis and prediction of the NPL rate in the example of MS Bank, it can be seen that the NPL rate of Chinese financial institutions is now showing a year-on-year increase in the undesirable trend under the influence of FinTech, indicating that FinTech has a negative impact on bank risk management. Therefore, it is necessary to formulate relevant strategies in time to deal with the risk challenges brought by fintech. In the context of the deep integration of financial technology and various banking businesses, the pace of business innovation of banks has accelerated, and various new business models have begun to emerge, such as the "Quick Loan" launched by CCB and the "Flash Loan" launched by China Merchants Bank, which are all credit loan products designed based on the analysis of customer big data. These innovative products will inevitably have a positive effect on the current income of banks, but the ensuing pressure on risk prevention and control will increase. Taking credit loans of various banks as an example, banks give credit loans to customers based on the risk of customer data, which objectively amplifies the bank's credit risk, while the bank's credit analysis of customers comes from the multi-dimensional collection of customer data, and there are data fallacies, changes in the credit level of the customer and other factors in the process, so the innovation and development of fintech improves the bank's exposure to operational risk and enhances the difficulty of risk management, which requires banks to pay great attention to the development of fintech along with the development of risk management technology, talents and talents. The difficulty of risk management requires banks to pay great attention to the improvement of risk management technology, talents, systems and other aspects while developing fintech to cope with the new risk management pressure.

Table 6. The predicted value of the non-performing loan ratio by the end of 2022

	VaR

	95%	99%
White noise	0.7369%	0.7422%
$AR(1)$	0.7963%	0.8031%
$ARMA(1,1)$	0.7988%	0.8055%

5. Policy recommendations

Different types of commercial banks should adopt different development modes in the face of the impact of fintech according to their own operating characteristics. Large state-owned commercial banks and joint-stock commercial banks should further strengthen their mastery and application of emerging technologies such as artificial intelligence, big data and blockchain, fully integrate fintech with product design, service optimization and customer experience, build an intelligent and personalized financial service ecosystem, and create core competitiveness through fintech to achieve sustainable development. Urban commercial banks take advantage of their local strengths, closely focus on the characteristics of regional economic development, focus on small and micro enterprises, community residents and other segments of the market, provide differentiated products and services through fintech, accurate marketing, and help local economic characteristics. Rural commercial banks, as the main financial force serving the “three rural areas”, should actively embrace the changes in financial technology, continue to strengthen strategic cooperation with financial technology companies, Internet finance companies, etc., and continuously innovate the functions of financial services, broaden the coverage of financial services, improve the availability of services, and contribute to the revitalization of the countryside and the high-quality development of the rural economy, so as to achieve their own operational efficiency. Contribute to the promotion of rural revitalization and high-quality development of rural economy, and realize the win-win situation between the improvement of its own operation efficiency and the development of local economy.

Under the financial technology model, new forms, new technologies and new products are emerging, and the boundaries between financial business and technological innovation are becoming increasingly blurred, and the traditional regulatory model according to the type of institution has been difficult to adapt to the requirements of the new situation, and the regulatory authorities should attach great importance to the potential impact of the development of financial technology on the stability of the financial system, accelerate the improvement of the legal system for the regulation of financial technology, and build a regulatory framework that adapts to the requirements of the new era. Keeping up with the pace of technological innovation, anticipating risks in a forward-looking manner, formulating scientific and reasonable regulatory policies, guarding against systemic risks that may be triggered by fintech, providing solid institutional safeguards for the sound operation of China's commercial banks and the entire financial industry, and creating a fairer, more transparent, and healthier environment for development.

6. Conclusion

The study uses Monte Carlo simulation to realize the VaR calculation of fintech on banks' operational efficiency and risk management.

1) Fintech has a reverse effect on the operational efficiency of both big five banks and joint-stock banks, and the effect suffered by city commercial banks is positive.

2) The addition of fintech increases the NPL ratio of China's MS banks at the end of 2022 compared to the pre-addition period. the predicted value of the NPL ratio in 2022 by the three stochastic processes at 95% and 99% confidence is greater than that in 2021 (0.71%), indicating that fintech poses a risk management challenge for banks.

3) This paper argues that fintech should be reasonably guided and regulated mainly from the regulatory field, and scientific and reasonable regulatory policies should be formulated in order to prevent the systemic risks that may be triggered by fintech.

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