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The Impact of Commercial Banks' Fintech Development on Their Own Risk Management

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Abstract: *This study uses publicly available data from January 2011 to December 2020 drawn from the Wind database and the annual reports of nine major Chinese commercial banks—Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China, China Construction Bank, Bank of Communications, China Merchants Bank, China Minsheng Bank, China CITIC Bank, and Industrial Bank—to construct a fintech index for each year from 2011 to 2020. By empirically analyzing the relationship between this fintech index and the asset-to-capital ratio of these banks, the paper examines how fintech development affects the risk profile of commercial banks.*

Keywords: *Fintech; Commercial Banks; Risk Management*

1. Introduction

The explosive advance of financial technology is propelling commercial banks to accelerate digital transformation. Technologies led by artificial intelligence, big data, blockchain, and cloud computing are profoundly reshaping business models and service ecosystems. Fintech injects new growth momentum into banks by boosting operational efficiency, optimizing customer experience, and tapping long-tail markets, yet it simultaneously poses unprecedented challenges to traditional risk-management frameworks.

On the one hand, innovation-driven offerings such as internet lending, robo-advisory, and open-banking introduce intricate algorithmic, data-security, and cross-contagion risks. On the other hand, the digitization process generates vast amounts of unstructured data, real-time transaction scenarios, and decentralized finance models, making credit, liquidity, and operational risks more opaque and dynamic. Critically, while fintech enhances risk-identification capabilities, it can also trigger systemic risk through technical flaws, model homogeneity, or regulatory lag.

Against this backdrop, exploring how fintech affects banks' risk-management effectiveness via the dual pathways of technological empowerment and risk transmission is theoretically vital for balancing innovation with stability and for building an intelligent risk-control architecture suited to the digital era. Existing studies concentrate mainly on localized benefits of technology adoption, leaving a gap in reconstructive analysis of the overall risk-management framework-precisely the area this research aims to break new ground in.

2. Theoretical Analysis and Research Hypotheses

The rapid development of fintech is profoundly reshaping the global financial system. While it brings significant efficiency improvements and cost optimization, it also introduces more complex systemic risks. This transformative force impacts financial stability through three core pathways:

First, technological innovation accelerates the process of financial globalization while simultaneously constructing tighter risk transmission networks. The widespread application of blockchain and distributed ledger technology facilitates cross-border capital flows but also establishes a globally interconnected risk propagation mechanism. Regional financial turbulence may rapidly escalate into systemic crises through digital channels.

Second, fintech is redefining the market landscape of traditional financial institutions. New market participants such as third-party payment providers and fintech platforms are rapidly expanding their business territories with technological advantages. However, their relatively weak capital buffers and risk management systems may become vulnerable links in the financial chain.Of particular concern is how

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AI-driven high-frequency trading and robo-advisors are altering market behavior patterns. Algorithmic homogenization may trigger a "herding effect," exacerbating market volatility[1]. While big data risk control enhances credit assessment efficiency, it may also lead to risk misjudgments due to data biases or model flaws. Furthermore, the rapid advancement of fintech has given rise to regulatory lags[2]. Challenges such as insufficient cross-border regulatory coordination and inadequate understanding of technological risks are becoming increasingly prominent. These intertwined factors mean that while fintech promotes the development of inclusive finance, it also fosters new risk paradigms. There is an urgent need to establish a macroprudential regulatory framework and international coordination mechanisms tailored to these evolving dynamics[3].

The development of fintech is reshaping the risk management landscape of commercial banks, bringing efficiency improvements and business innovation while also introducing multidimensional risk challenges.

From the perspective of risk transmission mechanisms, the globalized nature of fintech intensifies the interconnectedness of the financial system, accelerating the spread of systemic risks through tighter interbank networks. Localized risks may trigger chain reactions. At the technological application level, while big data risk control and intelligent algorithms enhance risk assessment capabilities, threats such as data security risks, model homogenization, and system failure risks have significantly increased, posing adaptability challenges to traditional risk management frameworks[4].

Particularly noteworthy is how the expansion of inclusive finance has increased credit risk exposure due to long-tail customers, while innovative financial instruments have complicated market risk measurement. Coupled with external factors such as exchange rate fluctuations and commodity price volatility, these developments collectively raise banks' risk-taking levels. Additionally, risks associated with data migration during technological upgrades, information storage security, and operational risks during system transitions may threaten the stability of commercial banks' information systems.

These changes require banks to not only address the digital transformation of traditional risks but also guard against technology-specific risks inherent in fintech, necessitating the development of a more resilient and intelligent risk control system.

Based on the above theoretical framework, this paper proposes the following hypotheses regarding the impact of fintech on commercial bank risk management:

Hypothesis 1: Commercial bank risk is significantly influenced by fintech, and the two are positively correlated—bank risk increases as fintech continues to develop.

Hypothesis 2: Commercial bank risk is significantly influenced by fintech, and the two are positively correlated—but bank risk decreases as fintech continues to develop.

Hypothesis 3: The impact of fintech on commercial bank risk is relatively minor.

3. Empirical analysis

3.1 Data preparation

To ensure the scientific rigor and reliability of the research, the study draws its sample from nine of the country's largest commercial banks: China Merchants Bank, Industrial Bank, China CITIC Bank, China Minsheng Bank, Bank of Communications, China Construction Bank, Bank of China, Agricultural Bank of China, and Industrial and Commercial Bank of China. The data cover the period 2011–2020 and are sourced from the Wind database and the annual reports of each bank.

3.2 Core Variable Definitions

Variables were selected through a systematic design. The dependent variable is the asset-to-capital ratio (total assets divided by liabilities plus shareholders' equity), which serves as a proxy for bank risk-taking. Compared with the conventional Z-score or EDF default probability, this ratio more comprehensively captures the risk profile of Chinese commercial banks.

The key explanatory variable is the FinTech adoption index. Constructed from a financial-function perspective, the index goes beyond the narrow focus on internet-based payment services found in the literature and incorporates dimensions such as risk management and channel development.

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Control variables are drawn from both micro- and macro-level dimensions. Micro-level controls include bank size (logarithm of total assets) and profitability (ROE); macro-level controls comprise GDP growth and financial-market development (stock-market capitalization-to-GDP ratio). Bank size reflects the trade-off between scale economies and diversification benefits, ROE captures the link between profitability and risk appetite, and the macro indicators account for how the economic environment influences banks' risk-taking.

After testing for multicollinearity using the variance inflation factor (VIF), GDP growth, financial-market development, and ROE were retained as the core control variables. This parsimonious specification ensures the model isolates the effect of FinTech on bank risk while holding key internal and external confounders constant.

3.3 Model Specification

Using SPSSAU software, we construct a Baidu-Index-based FinTech index by aggregating the daily search frequencies of a predefined keyword lexicon. The following regression model is specified to test the impact of FinTech adoption on bank risk-taking.

3.4 Construction of the FinTech Index

3.4.1 Factor Analysis Approach

As shown in Table 1, we will conduct factor analysis using SPSSAU, synthesizing five keywords: "online banking," "mobile payment," "internet finance," "fintech," and "mobile banking."

Table 1: FinTech keyword data

Keywords	online banking	mobile payment	internet finance	fintech	mobile banking
2011	6868	384	1	23	1730
2012	6217	557	60	37	2778
2013	4543	652	740	44	2989
2014	4123	749	2052	46	3591
2015	3755	794	3215	77	3994
2016	2571	751	2408	226	2864
2017	2024	1040	2245	481	2330
2018	1918	854	1853	523	1782
2019	1367	562	1050	499	1554
2020	1173	394	1048	873	1725

3.4.2 Sphericity test

Before conducting factor analysis, we need to check whether the data are appropriate by computing the Kaiser–Meyer–Olkin (KMO) measure and performing Bartlett's test. As shown in Table 2, first, the significance value of Bartlett's test is below 0.10, indicating that the data can be used. Although the conventional rule of thumb requires a KMO statistic greater than 0.6, our value of 0.574 is very close to this threshold. Given the limited availability of data, we relax the criterion slightly and conclude that the dataset is suitable for factor analysis.

Table 2: KMO and Bartlett's Test

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy		0.574
Test	Approximate chi-square	29.532
	Degrees of freedom	10
	Significance	0.001

According to Table 3, the central idea of factor analysis is to distill the most relevant information from multiple indicators and reduce dimensionality. In the variance-extraction step, we retain components whose eigenvalues exceed 1. This criterion yields two components whose cumulative explained variance reaches 89.244 %—approximately 90 %. Consequently, retaining these two components is strongly justified, as they capture nearly all of the variation present in the original variables.

After deciding to retain two components, we obtain the component-score coefficients to determine each variable's weight. These weights are then combined with the components' explained-variance shares in a weighted average, yielding the final FinTech index.

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Table 3: Component Score Coefficient Matrix

Component Score Coefficient Matrix		
	Component	
	1	2
x1	-.175	.392
x2	.391	-.010
x3	.425	-.042
x4	-.024	-.439
x5	.287	.318

According to Table 4, below are the FinTech index values from 2011 to 2020 computed with SPSSAU.

Table 4: FinTech Index Indicators

FinTech	2011	2012	2013	2014	2015
	-0.461112385	0.043017311	0.244622198	0.772825912	1.133361967
	2016	2017	2018	2019	2020
	0.365224082	0.19578142	-0.286773715	-0.805003656	-1.201948011

3.5 Regression Analysis

Through factor analysis and related companies using SPSSAU, the variables required for this study were ultimately obtained. According to Table 5, below is the statistical description of the variables used in this study. The sample data consists of 90 observations, where the asset-to-capital ratio shows significant variation among companies, with an overall moderate level. The fintech index exhibits a gradual positive and negative symmetry centered around 0, with the maximum and minimum values. The degree of financial market development is generally at a medium to high level. The GDP growth rate has shown progress during this period, and the ROE is also at a moderate level overall.

Table 5: Regression Analysis

Variable	Obs	Mean	Std.Dev.	Min	Max
Asset-to-capital ratio	90	13.08	3.866	1.705	20.75
Fintech	90	-9.89e-07	0.675	-1.202	1.133
Financial market development	90	0.641	0.151	0.456	0.880
GDP	90	6.849	1.770	2.300	9.551
roe	90	16.14	4.492	6.545	25.67

Table 6 indicates that, before conducting the regression, the model requires a multicollinearity test. If the explanatory variables can be linearly expressed by one another, it may lead to collinearity issues, affecting the estimation results and causing the least squares method to fail. Therefore, the Variance Inflation Factor (VIF) is used to detect multicollinearity. Generally, a VIF value below 10 is considered an acceptable level of collinearity for the model. In this study, the VIF values among variables range between 2 and 5, indicating that the degree of multicollinearity is within tolerable limits for regression analysis.

Table 6: Regression Analysis

Variable	VIF	1/VIF
Asset-to-capital ratio	2.34	0.426
Fintech	3.41	0.292
Financial market development	4.60	0.217
GDP	2.15	0.464
MeanVIF	3.13	

Table 7 indicates that,first, the F1 test is conducted with the null hypothesis that the pooled model is superior to the random effects model. The p-value is less than 0.1, so the null hypothesis is rejected, and the random effects model should be used. Next, the F2 test is performed. The initial conjecture was that the pooled model performs better than the fixed effects model. The p-value is less than 0.1, so the null hypothesis is rejected, indicating that the fixed effects model should be used here. Finally, the Hausman test is conducted, with the null hypothesis that the random effects model is superior to the fixed effects model. The p-value here is not greater than 0.1, so the null hypothesis is rejected, and it is ultimately determined that the fixed effects model should be used to carry out the subsequent research.

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Table 7: The model specification test

Test Method	Null Hypothesis	Statistic	P-value	Conclusion
F1 Test	Pooled is better than random effects	284.61	0	Reject
F2 Test	Pooled is better than fixed effects	78.61	0	Reject
Hausman Test	Random effects are better than fixed effects	13.21	0.0103	Reject

The regression results based on the fixed-effects model indicate that the model is statistically significant overall ($F=54.36$, $p<0.1$), with a goodness-of-fit (R^2) of 0.688.

Fintech development exhibits a significant negative impact on the capital adequacy of commercial banks ($\beta=-1.029$, $p<0.05$), suggesting that the application of fintech—through smart algorithms and data analytics—optimizes banks' risk management processes, thereby reducing capital reserve requirements. Bank profitability (ROE) shows a significantly positive correlation with the asset-to-capital ratio ($\beta=0.422$, $p<0.01$), reflecting that more profitable banks tend to expand their business scale.

Table 8 indicates that although the coefficients for financial market development and GDP growth rate are 0.159 and -0.154, respectively, neither is statistically significant.

The empirical results demonstrate that fintech development significantly lowers capital adequacy requirements by improving banks' risk management efficiency, whereas traditional macroeconomic factors have a relatively limited impact on bank capital structure.

Table 8: Empirical Analysis

VARIABLES	(1)
	Asset-to-capital ratio
Fintech	-1.029**
	(0.451)
Financial market development	0.159
	(3.674)
GDP	-0.154
	(0.206)
roe	0.422***
	(0.133)
Constant	5.334
	(2,622)
STKCD	YES
F	54.36***
R2	0.688
Observations	90

4. Conclusions

This study empirically examines the FinTech development of nine major Chinese commercial banks from 2011 to 2020 and its impact on their risk management. The findings indicate a significant negative correlation between a FinTech index and banks' asset-to-capital ratio, demonstrating that FinTech adoption effectively reduces bank risk and markedly enhances risk-management capabilities. Although large state-owned and joint-stock banks lead in FinTech deployment, the risk-mitigating benefits are positive across all sample banks; nonetheless, owing to differences in size, market position, and resource allocation, the magnitude of these benefits varies among individual institutions.

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